Performance Enhancement of Smart Antennas Algorithms for Mobile Communications System

Thamer M. Jamel

Abstract— This paper proposes new two smart antennas algorithms based on a combined method for performance enhancement of mobile communications systems. The first proposal combination method includes merging pure Conjugate Gradient Method (CGM) with pure Normalized Least Mean Square (NLMS) algorithms, so that the new algorithm is called as CGM-NLMS. While the second proposed algorithm will merge pure CGM with Modified NLMS algorithm so that this algorithm is called as CGM-MNLMS algorithm. The MNLMS algorithm is regarded as variable regularization parameter $\varepsilon(k)$ that is fixed in the conventional NLMS algorithm. The regularization parameter $\varepsilon(k)$ uses a reciprocal of the estimation error square of the update step size of NLMS instead of fixed regularization parameter (ε).

With the new proposed (CGM-NLMS) and (CGM-MNLMS) algorithms, the estimated weight coefficients, which are acquired from the first stage (CGM) algorithm, are stored and then used as initial weight coefficients for NLMS (or MNLMS) algorithm processing. Through simulation results of adaptive beamforming system using fading channel with a Jakes power spectral density channel model, the two new proposed algorithms provides fast convergence time, higher interference suppression capability and low level of Mean Square coefficients Deviation (MSD) and minimum Mean Square Error (MSE) at the steady state compared with the pure CGM and pure NLMS algorithms.

Keywords— Smart Antennas, Conjugate Gradient Method (CGM), Least Mean Square (LMS), Normalized LMS (NLMS), Time-varying regularization parameter, Rayleigh fading channel, Jakes model.

I. INTRODUCTION

THE significant feature of Widrow and Hoff (1960) Least Mean Square (LMS) algorithm is its simplicity [1]. Moreover, it does not require measurements of the pertinent correlation functions, nor does it require a matrix inversion [1]. The main limitation of the LMS algorithm is its relatively slow rate of convergence [1]. In order to increase the convergence rate, LMS algorithm is modified by normalization, which is known as normalized LMS (NLMS) [1, 2]. We may view the normalized LMS algorithm as an LMS algorithm with a time varying step-size parameter [1].

Many approaches of time varying step size for NLMS algorithm, like Error Normalized Step Size LMS (ENSS), Robust Variable Step Size LMS (RVSS) [3], and Error - Data

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Normalized Step Size LMS (EDNSS) [3] and others are reported [3-15]. The generalized normalized gradient descent (GNGD) algorithm in 2004 [6], used gradient adaptive term for updating the step size of NLMS [6]. The first free tuning algorithm was proposed in 2006 [7] which used the MSE and the estimated noise power to update the step size [7]. The robust regularized NLMS (RR-NLMS) filter is proposed in 2006 [8], which use a normalized gradient to control the regularization parameter update [8]. Another scheme with hybrid filter structure is proposed (2007) in order to performance enhancement of the GNGD [9]. The noise constrained normalized least mean squares (NC-NLMS) adaptive filtering is proposed in 2008 [10] which is regarded as a time varying step size NLMS [10]. Another free tuning NLMS algorithm was achieved in 2008 [11,12] and it is called generalized square error regularized NLMS algorithm (GSER) [10,11]. The inverse of weighted square error is proposed for variable step size NLMS algorithm in 2008 [13]. After that the Euclidian vector norm of the output error was suggested for updating a variable step size NLMS algorithm in 2010 [14]. Another nonparametric algorithm that used mean square error and the estimated noise power is presented in 2012 [15].

All these algorithms suffer from preselect of different constant parameters in the initial state of adaptive processing or have high computational complexity. In this paper, a Modified Normalized Least Mean Square algorithm (MNLMS) is proposed which is also tuned free (i.e. Nonparametric). It used time varying regularization $\varepsilon(n)$ instead of fixed value (ε) [16].

The gradient based directions method in some cases has slow convergence rate. In order to overcome this problem, Hestenes and Stiefel developed conjugate gradient method (CGM) in the early 1950s [17]. The CGM suffers from that the rate of convergence depends on the conditional number of the matrix $\overline{A}$. Therefore, many modifications have been proposed to improve the performance of the CG algorithm for different applications [18].In [19]; the step size can be replaced by a constant value or with a normalized step a size [19].Moreover the preconditioning process is used to increase the convergence rate of the CGM algorithm by change the distribution of the eigenvalues of $\overline{A}$ and clustered them around one point.

In 1997, spatial and time diversity for CGM algorithm is used to obtain an algorithm for smart antennas in mobile communication systems [20]. In 1999,they solved the problem of applying CGM for a small number of both snapshots and the array elements by proposing new forward and backward

CGM (FBCGM) and multilayer (WBCGM) methods [21]. In 2013, interference alignment in time-varying MIMO (multiple input and multiple-output) interference channels was achieved by applying an approach based on the conjugate gradient method combined with metric projection is applied for [22]. In 2013, adaptive block least mean square algorithm (B-LMS) with optimally derived step size using conjugate gradient search directions was proposed to minimize the mean square error (MSE) of the linear system [23].

Although the pure CGM has better performance compared with a pure NLMS algorithm, but we can obtain further performance enhancement when we combine these algorithms together in one algorithm. This paper presents a new approach to achieve fast convergence, higher interference suppression capability and low level of MSD, and MSE. The proposed algorithms involve the use of a combination of CGM (as first stage) with NLMS (or MNLMS) algorithm (as second stage). In this way, the desirable fast convergence, good interference suppression capability of CGM is combined with the good tracking capability of variable step size method and low level of MSD, and MSE of NLMS (or MNLMS) algorithm

The paper consists of the following sections: The next section, introduces an overview of classical adaptive algorithms. In section III, the proposed algorithm (MNLMS) will be presented and in section IV, the analysis of the time varying step size of MNLMS algorithm will be given. In section V, the CGM algorithm will be presented. Section VI, will give the proposed two combination algorithms. In section VII, the simulation results of the proposed algorithms as well as pure CGM and pure NLMS algorithms are presented. In section VIII, an intuitive justification for performance enhancement of the proposed two algorithms will be presented. Finally, in the last section, we conclude the paper according to the simulation results.

II. AN OVERVIEW OF CLASSICAL ADAPTIVE ALGORITHMS

Smart antennas al system of M-element array can be drawn as in Fig. 1. This figure shows that, the weight vector $\overline{w} = [w_1 \, w_2 \, ... \, w_M]^T$ must be modified in such a way as to minimize the error while iterating the array weights [24].The signal $\overline{s}(k)$ and interferers $i_1(k), i_2(k), ... i_N(k)$ are received by an array of M elements with M potential weights [24]. Each received signal at element m also includes additive Gaussian noise. Time is represented by the k_{th} time samples. Thus, the weighted array output can be given in the following form [24]:

$$y(k) = \overline{w}^T(k).\bar{x}(k) \tag{1}$$

Where the operator T denotes to the vector transpose, and $\overline{x}(k)$ is input signal vector which is equal to:

$$\bar{x}(k) = \bar{a}_0 \bar{s}(k) + [\bar{a}_1 \, \bar{a}_2 \, ...\bar{a}_N] . \begin{bmatrix} i_1(k) \\ i_2(k) \\ \vdots \\ i_N(k) \end{bmatrix} + \bar{n}(k)$$
$$= \bar{x}_s(k) + \bar{x}_i(k) + \bar{n}(k) \tag{2}$$

With

$\overline{x}_s(k)$ is desired signal vector.

$\overline{x}_i(k)$ is interfering signal vector.

$\overline{n}(k)$ is zero mean Gaussian noise for each channel.

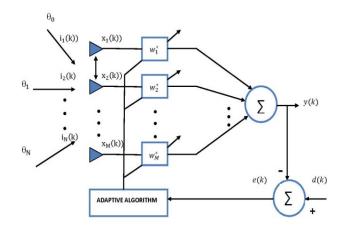$\overline{a}_i$ is M-element array steering vector for θ_i direction of arrival.

Fig. 1. Block diagram of Smart Antennas System.

An error signal is defined as the difference of desired signal d(k) and output signal y(k)[24]

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

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

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

The parameter μ is constant and is known as the step size [24]. In order to guarantee stability of the LMS algorithm; the step size parameter is should be bounded by [25].

$$0 < \mu < \frac{2}{tr\,[\overline{R}]} \tag{5}$$

Where $\overline{R}$ is the correlation matrix. Note that all the elements on the main diagonal of $\overline{R}$ equal to $r(0)$ .Since $r(0)$ is itself equal to the mean square value of the input at each of the M- taps in FIR filter, then

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

The LMS algorithm uses a constant step size μ proportional to the stability bound:

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

Since knowledge of the signal statistic $r(0)$ is not available, a temporary estimate of the $r(0)$ can be computed by:-

$$r(0) = \frac{1}{M} \, \overline{x}^T(k)\overline{x}(k) \tag{8}$$

Then the "normalized" $\mu_{MAX}(k)$ is given by

$$\mu_{MAX}(k) = \frac{2}{\bar{x}^T(k)\bar{x}(k)} \qquad (9)$$

This is the upper limit of step size; therefore, the practical equation for the step size used for NLMS is [25]:

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

Where u_0 is a small positive constant and should be bound to guarantee the convergence of the NLMS algorithm [25],

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

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

The fixed regularization parameter $\varepsilon > 0$ is added to overcome the problem of dividing by small value for the $\bar{x}^T(k)\bar{x}(k)$ [24].

III.   MODIFIED NORMALIZED LEAST MEAN SQUARE ALGORITHM (MNLMS)

The proposed MNLMS algorithm introduces a new way of choosing the step size [16]. The small constant ε in the NLMS algorithm has fixed effect in step size update parameter and may cause a reduction in its value. This reduction in step size affects the convergence rate and weight stability of the NLMS algorithm. In MNLMS algorithm, the error signal may be used to avoid denominator being zero and to control the step size in each iteration[16]. According to this approach, the ε parameter can be set as:

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

The proposed new step size formula can be written as

$$\mu_{mnlms}(k) = \frac{\mu_0}{\varepsilon(k) + \|\bar{x}(k)\|^2} \qquad (13)$$

Clearly, $\mu_{mnlms}(k)$ is controlled by normalization of both reciprocal of the squared of the estimation error and the input data vector. Therefore, the weight vector of MNLMS algorithm is

$$\bar{w}(k+1) = \bar{w}(k) + \frac{u_0}{\varepsilon(k) + \|\bar{x}(k)\|^2} e(k)\bar{x}(k) \qquad (14)$$

As can be seen from (13), the step size of MNLMS reduces and increases according to the reciprocal of the squared estimation error and input tap vectors.

In other word, when the error signal is large at the beginning of the adaptation process, then the $\varepsilon(k)$ is small and the step size is large in order to increase the convergence

rate. However, when error signal is small in steady state, then the $\varepsilon(k)$ is large and the step size is small in order to get a low level of misadjustment at steady state as shown in Fig.2. This prevents the update weights from diverging and makes the MNLMS more stable and converges faster than NLMS algorithms.
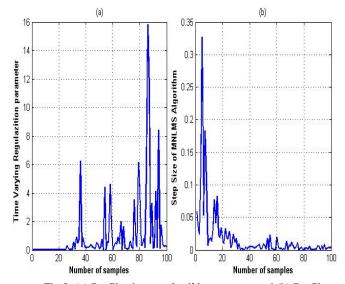

Fig.2. (a) Profile change of $\varepsilon(k)$ parameter and (b) Profile change of step size parameters ($\mu_{mnlms}(k)$) of MNLMS algorithm.

IV.   ANALYSIS OF THE PROPOSED MNLMS ALGORITHM

This section, will give an approximate performance analysis for the proposed MNLMS algorithm using a similar approach used in [4, 25].The weight coefficients of the proposed algorithm are updating as in (17). This is rewritten as:

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

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

$$\bar{w}(k+1)^* = \bar{w}(k)^* + p(k) \qquad (16)$$

Where $p(k)$ is the disturbance zero-mean white process [4]. Moreover, let $\zeta(k)$ represents the optimum estimation error process defined as [4]:

$$\zeta(k) = d(k) - \bar{x}^T(k)\bar{w}(k)^* \qquad (17)$$
or
$$d(k) = \zeta(k) + \bar{x}^T(k)\bar{w}(k)^* \qquad (18)$$

Let $\bar{v}(k)$ represents the coefficient misadjustment vector (error vector) defined as [25]:

$$\bar{v}(k) = \bar{w}(k) - \bar{w}(k)^* \qquad (19)$$

Substitutes (18 and 19) in (3) for $d(k)$ and $\bar{v}(k)$ respectively, then e(k) in (3) becomes:

$$e(k) = \zeta(k) + \bar{x}^T(k)\bar{w}(k)^* - \bar{x}^T(k)\bar{w}(k)$$
$$e(k) = \zeta(k) - \bar{v}^T(k)\bar{x}^T(k) \qquad (20)$$

Taking expected value of (20) after squaring it, then

$$E[e^2(k)] = \xi_{min} + \sigma^2(\bar{x})tr[\overline{G}(k)] \qquad (21)$$

Where $\xi_{min} = E[\zeta^2(k)]$ represents the MMSE (minimum mean-square error) [4], $\sigma^2(\boldsymbol{x}) = E[\bar{x}(k)^2]$, and $\overline{G}(k) = E[\bar{v}(k)\bar{v}^T(k)]$ is the expected value of the coefficient misadjustment vector (error vector) [4]. Substituting (18), (19), and (20) into (15), we can easily show that

$$\bar{v}(k+1) = (I - \mu_{mnlms}(k)\bar{x}^T(k)\bar{x}(k))\bar{v}(k) + \mu_{mnlms}(k)\bar{x}(k)\zeta(k) - p(k) \qquad (22)$$

Now assume that, $\mu_{mnlms}(n)$ is uncorrelated with $\bar{x}(k)$, and $\zeta(k)$ respectively, and the term $p(k)$ is zero mean [4, 25], then the expected value of the weight vector is given by [4]:
$$E[\bar{v}(k+1)] = [I - E[\mu_{mnlms}(k)]E[\bar{x}^T(k)\bar{x}(k)]]E[\bar{v}(k)] \qquad (23)$$

Then the convergence of the proposed algorithm is guaranteed if the expected value of the step size parameter is within the following bound:

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

V. CONJUGATE GRADIENT METHOD (CGM)

The goal of CGM algorithm is to iteratively search for the optimum solution by choosing conjugate (perpendicular) paths for each new iteration [24]. CGM is an iterative method whose goal is to minimize the quadratic cost function [24]

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

Where $\overline{A}$ is the K x M matrix of array snapshots, (K = number of snapshots and M = number of array elements). $\bar{d} = [d(1)\, d(2)\, ...\, d(K)]^T$ is the desired signal vector of K snapshots. It can be shown that the gradient of the cost function is [24]:

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

Starting with an initial guess for the weights $\bar{w}(1)$, then the first residual value $\bar{r}(1)$ after at the first guess (iteration =1) is given as [24]:

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

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

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

The general weight update expression is given by [24]:

$$\bar{w}(k+1) = \bar{w}(k) + \mu_{CGM}(k)\overline{D}(k) \qquad (29)$$

Where μ_{CGM} is the step-size of CGM and is given by [24]:

$$\mu_{CGM}(k) = \frac{\bar{r}^H(k)\,\overline{A}\,\overline{A}^H\,\bar{r}(k)}{\overline{D}^H\,\overline{A}^H\overline{A}\,\overline{D}(k)} \qquad (30)$$

The residual vector update is given by [24]:

$$\bar{r}(k+1) = \bar{r}(k) + \mu_{CGM}(k)\overline{A}\,\overline{D}(k) \qquad (31)$$

and the direction vector update is given by [24]:

$$\overline{D}(k+1) = \overline{A}^H\bar{r}(k+1) - \alpha(k)\overline{D}(k) \qquad (32)$$

A linear search is used to determine α (k) which minimizes $j(\bar{w}(k))$.

$$\alpha(k) = \frac{\bar{r}^H(k+1)\,\overline{A}\,\overline{A}^H\,\bar{r}(k+1)}{\bar{r}^H(k)\,\overline{A}\,\overline{A}^H\,\bar{r}(k)} \qquad (33)$$

Thus, the procedure to use CGM is to find the residual and the corresponding weights and update until convergence is satisfied.

VI. TWO NEW PROPOSED COMBINATION ALGORITHMS

The two proposed algorithms can summarized as the following
1.The first proposed algorithm is called CGM-NLMS which is a combination of CGM and NLMS algorithms. The NLMS algorithm uses the weight vector that calculated by the CGM algorithm as initial value to calculate the final optimal weight.
2.The second proposed algorithm is called CGM-MNLMS. It makes use of two individual algorithm stages, based on the CGM and the proposed MNLMS algorithms.

With the proposed (CGM-NLMS) and (CGM-MNLMS) algorithm scheme, the estimated weight coefficients, obtained from the first CGM algorithm, is storage, and then they used as initial weight coefficients for NLMS (or MNLMS) algorithm processing. In this way, the NLMS weight coefficients will not be initiated with zero value, but with previously estimated values that are obtained from the first algorithm (CGM). Table 1 shows the step sequence for both proposed algorithms.

VII. SIMULATION RESULTS

In this section, the pure CGM , pure NLMS , CGM-NLMS , and CGM-MNLMS algorithms are simulated and investigated for smart antennas applications in mobile communications system.

Table 1 CGM-NLMS and CGM-MNLMS algorithm

Set the parameters: K , AOA0, AOA1, AOA2, the order of the FIR and the number of array elements ; Generate the desired and interference signals;   Step 0 : Initialization (CGM as the first stage)

Get input data of K snapshots.
Set $\overline{w(0)} = [0,0,.....,0]^T$
Step 1 : For k= 1, 2, ….. K/2
Initialize columns of $\overline{x}$ matrix of input data as $\overline{x}(:,k) = x(k)$
Define matrix of array values for K time samples $\overline{A}$,set;
$\overline{r}(1) = \overline{d} - \overline{A}\overline{w}(1)$; $\overline{D}(1) = \overline{A}^H \overline{r}(1)$;
Step 3: for k=2 , 3 , … , K/2
Compute the following:
$\mu_{CGM}(k)$; update the weight coefficients as: $\overline{w}(k+1) = \overline{w}(k) + \mu_{CGM}(k)\overline{D}(k)$;
Update CGM parameters $\overline{r}(k+1)$; $\alpha(k)$; $\overline{D}(k+1)$;
End
Store $\overline{w}(k+1)$ as $\overline{w}(K/2)$ To be used as the initial weight for second stage, i.e. NLMS (or MNLMS) algorithm.
Second stage NLMS (or MNLMS) algorithm
Step 4 : Set $\overline{w}(1) = \overline{w}(K/2)$
Step 5 : For k= K/2, (K/2)+1, (K/2)+2….. K
Calculate the error signal as
$$e(k) = d(k) - \overline{w}^T(k)\,\overline{x}(k)$$
Update the weight coefficients as:
$\overline{w}(k+1) = \overline{w}(k) + \frac{\mu_0}{\varepsilon + \|\overline{x}(k)\|^2}e(k)\overline{x}(k)$ for NLMS
$\overline{w}(k+1) = \overline{w}(k) + \frac{u_0}{\varepsilon(k) + \|\overline{x}(k)\|^2}e(k)\,\overline{x}(k)$ for MNLMS
End

The performance of all algorithms is investigated in terms of interference suppression capability, MSD, and MSE learning curve. In all simulations presented here, a linear array consisting of M= 10 isotropic elements with $d = 0.5\lambda$ element spacing is used.The desired signal is cosine input signal $S(k) = \cos(2\pi ft(k))$ with $f = \frac{1}{T} = 900$ MHz and the iteration number are set to 200. The Desired Angle of Arrival (AOA) of the desired signal is set to $\theta_0 = 0^0$ and two interfering signals with AOAs, $\theta_1 = 30^0$, $\theta_2 = -30^0$ respectively. Signal to Noise ratio (SNR) is set to 30 dB, and Signal to Interference ration (SIR) is set to 10 dB. The average ensemble run is 100 for each 200 iterations.

The Mean Square coefficients Deviation (MSD) is computed for 100 average ensemble run as following:-
$$MSD = 10 * log_{10}(abs(\overline{w} - \overline{w}^*)^2 \quad dB \tag{34}$$

Where $\overline{w}$ the estimated weight is vector and $\overline{w}^*$ is the optimum weight vector, which can be computed as [1]:-

$$\overline{w}^* = \widehat{R}_x^{-1}\hat{r} \tag{35}$$

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

$$\widehat{R}_x = \overline{x}(k)^T \overline{x}(k) \tag{36}$$
$$\hat{r} = \overline{x}(k)^T \overline{d} \tag{37}$$

The Mean Square Error (MSE) is also computed for 100 average ensemble run.

A. The Simulation of the Rayleigh Fading Channel with Jakes Model

The Jakes fading model which is used in the simulations, also known as the Sum of Sinusoids (SOS) model, is a deterministic method for simulating time-correlated Rayleigh fading waveforms and is still widely used today.

The model assumes that N equal-strength rays arrive at a moving receiver with uniformly distributed arrival angles α_n, such that ray n experiences a Doppler shift $\omega_n = \omega_m \cos(\alpha_n)$, where $\omega_n = 2\pi f_c v/c$ is the maximum Doppler frequency shift, v is the vehicle speed, f_c is the carrier frequency, and c is the speed of light. As a result, the fading waveform can be modeled with No + 1 complex oscillator, where No = (N/2 - 1) /2. This leads to the equation [26]

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

Where, h is the waveform index, h=1, 2….N0 and λ is the wavelength of the transmitted carrier frequency. Here $\beta_n = \pi n/(N0 + 1)$. To generate the multiple waveforms, Jakes suggests using [26]

$$\theta_{nh} = \frac{\pi n}{N_0 + 1} + \frac{2\pi(h-1)}{N_0 + 1} \tag{39}$$

The output was shown as a power spectrum, with the variation of the signal power in the y axis and the sampling time (or the sample number) on the x axis [26]:

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

To present a classic case scenario, the velocity of a car is set to 80 km/h at 900 MHz. The Rayleigh Envelope that results for inputs of v = 80 km/h, f_c = 900 MHz, f_s =500 kbps, U =3and M = 1000000, is shown in Fig. 3, where U is the number of sub-channels and M is the number of channel coefficients.

B. Linear Radiation Pattern of algorithms

In order to properly assess the performance of smart antennas for mobile communication systems, an Additive White Gaussian Noise (AWGN) channel model is required that each received signal at element m in Fig. 1 includes only an additive, zero mean, Gaussian noise into account.
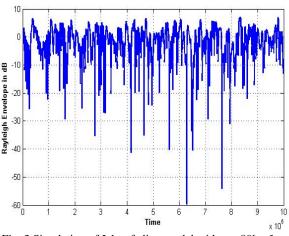
Fig. 3 Simulation of Jakes fading model with v = 80km/h.

Fig.5 Linear radiation patterns for pure CGM, pure NLMS and CGM-NLMS algorithms/Rayleigh channel

Fig. 4 presents the linear plot of the radiation pattern for the pure CGM, and pure NLMS algorithms. This figure shows that the pure CGM generates a deeper null of about −28 dB at interference angle -30° and 30° respectively. While NLMS generates a null of about −19 dB at interference angles.
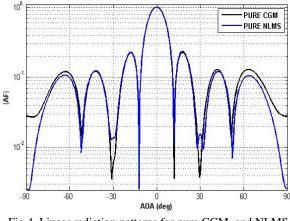
This means that the second proposed CGM-MNLMS algorithm has about 4 dB and 13 dB average improvement in interference suppression compared with pure CGM and NLMS algorithms. In other words, the second proposed algorithm achieved further performance enhancement compared with the first proposed algorithm.

Fig.4 Linear radiation patterns for pure CGM, and NLMS algorithms/Rayleigh channel

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Fig.6 Linear radiation patterns for pure CGM, pure NLMS and CGM-MNLMS algorithms/Rayleigh channel

Fig. 5 presents the linear plot of the radiation pattern for the pure CGM, pure NLMS and CGM-NLMS algorithms. This figure shows that the CGM-NLMS algorithm generates a deeper null of about −32 dB and -29 dB at interference angles -30^0 and 30^0 respectively which is higher than both pure CGM and pure NLMS algorithms. This means that the proposed CGM-NLMS algorithm has about 2.5 and 11 dB average improvement in interference suppression compared with pure CGM and pure NLMS algorithms respectively.

Fig. 6 presents the linear plot of the radiation pattern for the pure CGM, pure NLMS and CGM-MNLMS algorithms. This figure shows that the CGM-MNLMS algorithm generates a deeper null of about −32 dB at interference angles -30^0 and 30^0 respectively, which is higher than both pure CGM and CGM-NLMS algorithms.
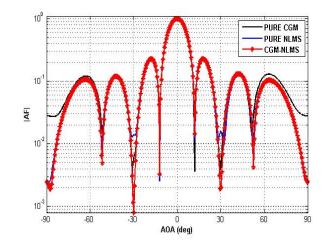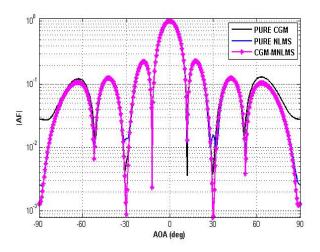
C. Estimation One Weight

Fig. 7 shows the magnitude estimation for one element weight (w4) for the first 20 iterations and one run only. As can be observed from this figure, the CGM –MNLMS has better performance compared with all other algorithms in terms of fast convergence rate and low level of misadjustment at steady state. In addition, the CGM-NLMS algorithm has better performance than both pure algorithms
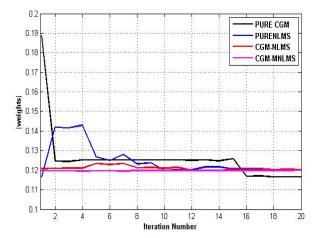
Fig. 7 One weight tracking for all algorithms/ Rayleigh channel.

D. MSD and MSE Learning Curve

Fig. 8 and 9 shows the (MSD) and MSE learning curves for all algorithms using ensemble average run of 100 for 200 iterations.
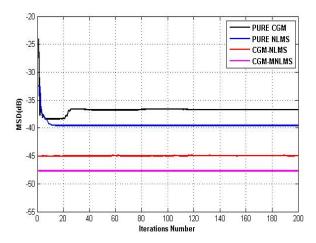

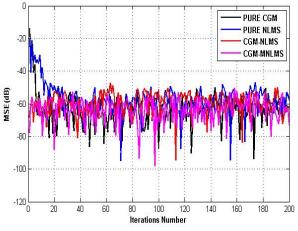Fig. 8 MSD plot for all algorithms / Rayleigh channel.

Fig. 9 MSE plot for all algorithms / Rayleigh channel

It can be seen that, both proposed algorithms have a faster convergence rate and minimum MSD at steady state compared with other algorithms. Moreover, the second proposed algorithm has minimum MSD at steady state compared with the first one.

VIII.   PERFORMANCE ANALYSIS OF THE PROPOSED ALGORITHMS

Intuitively justification for performance enhancement of the proposed two algorithms is as following;-

For NLMS (or MNLMS) algorithm, weights are initialized arbitrarily with $\overline{w}(0) = 0$ and then are updated. In order to speed up convergence, an initial weight vector, which has been coming through the CGM algorithm, is used. After the initial weights vector derivation, and the antenna beam is already scanned to the incident direction of the desired signal (by CGM), then the NLMS (or MNLMS) starts its operation.

When the NLMS (or MNLMS) algorithm begins adaptation, the antenna beam has already steered close to the approximate direction of the desired signal. Therefore the NLMS (or MNLMS) algorithm takes less time to converge compared with pure CGM or pure NLMS. After that, even if the signal environment changes, the two proposed combined algorithms are able to encounter these changes. In our paper, we consider a system which the environmental change is fast (Rayleigh fading channel with a Jakes model). Under this condition, with the signal environment change, NLMS (or MNLMS) algorithm can track the desired signal with fast convergence time because both NLMS and MNLMS algorithms have time varying step size.

Therefore, the two proposed algorithms combined the fast convergence rate capability and deep null of CGM with low level of MSD, and MSE, and also good tracking capability of time varying step size NLMS (or MNLMS). The final outcome of combined algorithms is fast convergence rate, high, deep null (interference suppression), low level of MSD, and MSE, and also high stability in steady state.

IX.   CONCLUSION

This paper presents a new approach to achieve fast convergence and higher interference suppression capability of the smart antennas application for a mobile communications system. The proposed algorithms involve the use of a combination of CGM in the first stage of combination with NLMS (or MNLMS) as second stage. In this way, the desirable fast convergence and high interference suppression capability of CGM is combined with better tracking and low level of MSD, and MSE capability of NLMS (or MNLMS). 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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