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Improved Adaptive Beamforming Algorithms for Wireless Systems

Veerendra Dakulagi[1]

Abstract

The classical least mean square (LMS) algorithm is a widely studied method for adaptive beamforming. It is well known for its lower computational complexity. However, fast and robust beamforming is not possible with the classical LMS method since it uses a constant step size. This nature hinders its applications in many advanced communication systems. Furthermore, this method degrades when the signal-to-noise ratio is rapidly changing. To circumvent these issues posed by the classical LMS method, two modified LMS beamformers are presented in this paper. We name these methods as M-LMS-1 and M-LMS-2. We present two new complex array weights to accelerate the rate of convergence. Computer simulations show that both methods present fast and robust beamforming. That is these algorithms have convergence improvement of about 37.5% and 50% over the standard LMS algorithm.

Keywords Adaptive antenna · Coherent sources · DOA · Toeplitz matrix · ULA

1 Introduction

In mobile communications, the fifth-generation (5 G) technology offers multigigabit data transmission. The evolution of the mobile networks from 1 G to the 6 G and the beyond is depicted in Fig. 1. One of the most promising technologies to improve the efficacy of the 5 G new radio (5GNR) are the smart antennas. Mobile edge computing (MEC) supports 5 G, especially, 5GNR, and exploits smart antennas to optimize coverage and minimize the need for hand-over from 5 G to 4 G RAN. 5GNR requires Smart Antennas since they use millimeter wave (mmwave) RF propagation [1]. Smart Antennas for 5GNR will significantly enhance the signal reception quality by focusing on the user signal where they are required the most.

Smart Antennas improve the signal quality, coverage, and capacity of 5 G, 5GNR, and 6 G and beyond by offering adaptive beamforming. This key technique of the smart antennas forms the major beam in the user direction and the nulls and sidelobes in the

✉ Veerendra Dakulagi
veerendra.gndec@gmail.com

1   Department of Electronics and Communication Engineering, Guru Nanak Dev Engineering
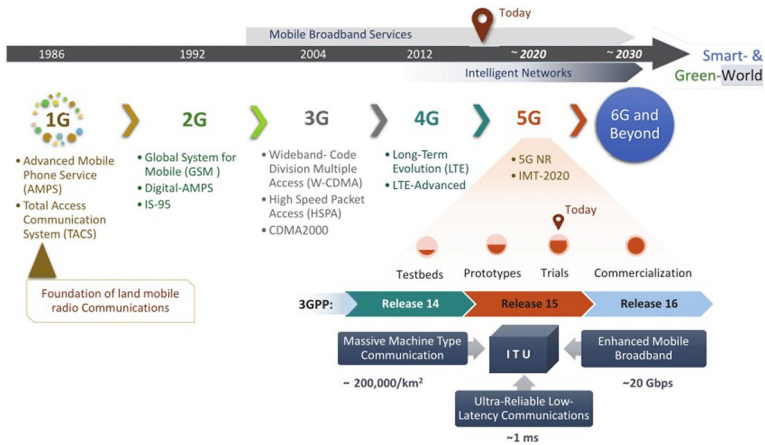   College, Bidar, Karnataka, India

Fig. 1 Evolution in the generations of mobile radio communication networks [1]

not required signal directions. A highly directed beam ensures high directivity and optimal bandwidth which are key requirements of various wireless communication systems including radar, sonar, satellite and mobile phones [2]–[8].

Smart antenna system (SAS) consists of an antenna array and signal processor, which makes it possible to transmit and receive the incoming signals in spacial sensitive and adaptive manner. This dramatically increases the capacity of wireless systems [9]–[12].

Numerous grave areas of smart antenna systems are listed as below [13]:

– Digital Signal processing algorithms.
– Wireless channel modeling and coding.
– Network performance for cellular communications.
– Antenna systems simulation and design.
– Processing of Space-time.

Smart antenna are used in wide applications, including, RADAR, sonar, satellite, MIMO based communication systems, Wifi and WiMAX applications, wireless Local area networks (WLAN) etc. Huge research work for enhancing the communication systems' performance is being carrying out worldwide. The smart antennas have emerged as frontier in the wireless communication industry to improve the quality, coverage and capacity [14]. In smart systems, the LMS beamformer has its own importance due to its due to robustness and simplicity. Nonetheless, this beamformer exploits fixed step size which inherently limits its use in many most adaptive filtering applications. As a result, this method has been constantly studied by many researchers to improve its performance.

One of the most popular methods is to deploy a varying step size of the classical LMS [15]. In this technique, the convergence is speeded up by using a large step size when the LMS method is away from its optimal solution. However, small step size is used when the method is close to the optimum [16].

To improve the convergence time of the classical LMS algorithm, two recent LLMS [17] and LLMS1 [18] were proposed. These methods combine LMS algorithms in two sections. Certainly, these methods show improvement over the classical LMS but demand to independent constant step size. This increases the complexity of the

algorithm [19]–[21]. Field trials and commercial products has taken place in recent year. A few examples are: Ericsson undertook one project in cooperation with German GSM1800 operator Mannesmann. It employed digital beam forming at the uplink and downlink, realizing an increase in capacity of 100–200%, as well as, an achievable range extension that is equivalent to 50% fewer sites.

European advanced communication technologies and services (ACTS) (TSUNAMI II project) dealing with the deployment of the smart antenna to DCS1800-based networks in Bristol, UK. The initial report findings from the project suggest a 54% range extension in rural environments and a reduction of interferences in the order of 30dB.

Bellofiere, employed smart antenna systems on mobile Ad-Hoc networks resulting in improved network capacity also; a 27% capacity improvement was shown when using smart antennas for IS-95 systems.

2 Array Signal Model

The considered ULA composed of M- antenna array is shown in Fig. 2. The antenna elements are separated by $\lambda/2$ to evade the grating lobe and the effect of mutual coupling. Let us assume that the $L \leq M$ user signals arriving from the far field directions are received by the considered ULA in presence of noise.

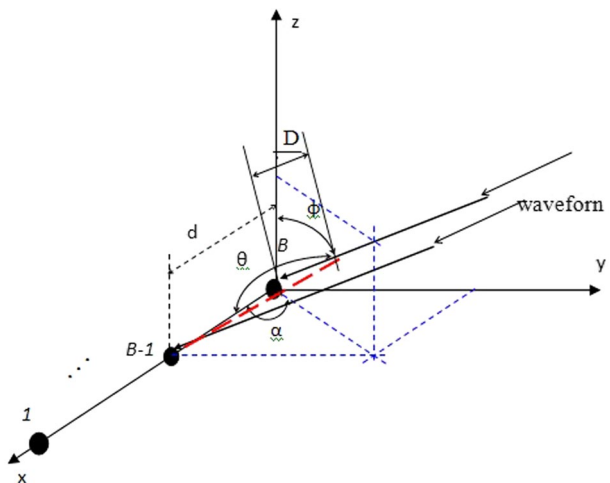The received signal can be expressed mathematically for the N sample as

$$\mathbf{x}(n) = \mathbf{A}(\theta)\mathbf{s}(n) + \boldsymbol{\zeta}(\boldsymbol{n}), \quad n = 1, 2, \cdots, N \tag{1}$$

where

$\mathbf{A}(\theta) = \left[\mathbf{a}(\theta_1), \mathbf{a}(\theta_2), \cdots, \mathbf{a}(\theta_L)\right]$ denotes the steering vectors of the received signal.

$\mathbf{s}(n) = \left[s_1(n), s_2(n), \cdots, s(n_L)\right]^T$ denotes the array covariance matrix and $\boldsymbol{\zeta}(\boldsymbol{n})$ represents the noise.

Let us write the steering vector as

Fig. 2 The ULA configuration used for smart antennas

$$\mathbf{a}\left(\theta_L\right) = \left[1, e^{j\left(\frac{2\pi}{\lambda}\right).sin\theta_L}, \cdots, e^{j\left(\frac{2\pi}{\lambda}\right)(M-1).sin\theta_L}\right]^T \tag{2}$$

Let us write the coverience matrix of the vector $\mathbf{x}(n)$ as

$$\mathbf{R} = \mathbb{E}\left[\mathbf{x}(n)\mathbf{x}^H(n)\right] = \mathbf{A}\mathbf{R}_s\mathbf{A}^H + \sigma_n^2\mathbf{I}_M \tag{3}$$

where $\mathbf{I}_M$ is the $(M \times M)$ identity matrix, $\mathbf{R}_s = \mathbb{E}\left[\mathbf{s}(k)\mathbf{s}(n)^H\right]$ denotes the signal covariance matrix and σ_n^2 is the noise power.

In practice, the expression (3) should be averaged over several snapshots as

$$\mathbf{R} = \frac{1}{N}\left[\sum_{n=1}^{N} \mathbf{x}(n)\mathbf{x}^H(n)\right] \in \mathbb{C}^{L \times L} \tag{4}$$

3 Proposed Methods

3.1 M-LMS1 Algorithm

In this work, we have modified the comples array weights of standard LMS algorithm as

$$\mathbf{W}(n+1) = \mathbf{W}(n) + \left[\frac{\mu(n)}{\alpha_1 \epsilon(n)\epsilon(n)^* + \left(1-\alpha_1\right)\epsilon(n)\epsilon(n)^*}\right] \cdot \left[\epsilon(n)^* \cdot \mathbf{x}(n)\right] \tag{5}$$

Here: α_1 is the shaping parameter=0.1

$\mathbf{W}(n)$ is the previous weights

$\mathbf{W}(n+1)$ is the updated array weights.

Furthermore, $\mu(n)$ is the step size which varies as the signal varies and $\epsilon(n)$ is the error signal. We write the expression of these parameters as

$$\mu(n) = \frac{\mu(n)_0}{\mathbf{x}(n)\mathbf{x}^H(n)} \tag{6}$$

$$\epsilon(\mathbf{W}(n)) = \epsilon(n) = \mathbf{x}(n+1)\mathbf{W}^H(n) - r(n+1) \tag{7}$$

where the $r(n+1)$ denotes the reference signal used for the tracking of the desired signal. The gradient estimate of the new LMS algorithm is given by [22]

$$\mathbf{g}(\mathbf{W}(n)) = 2\mathbf{R}(n+1)\mathbf{W}(n). \tag{8}$$

where

$$\mathbf{R}(n+1) = \left[\frac{n\mathbf{R}(n) + \mathbf{R}(n+1)}{n+1}\right]. \tag{9}$$

Finally, the array output is written as

$$y(n) = \mathbf{W}^H(n) \cdot \mathbf{x}(n) \tag{10}$$

3.2 M-LMS2 Algorithm

The modified complex weight update equation is expressed as:

$$\mathbf{W}(n+1) = \mathbf{W}(n) + \left[\frac{\mu(n)}{1 + \mu(n)\epsilon(n)\epsilon(n)^*\mathbf{x}(n)} \right] \cdot \left[\epsilon(n)^* \cdot \mathbf{x}(n) \right] \tag{11}$$

The array factor is expressed as

$$AF = \left[\sum_{i=1}^{L} \mathbf{W}_i^H exp(j2\pi\ sin(\varphi)) \right] \tag{12}$$

3.3 Results and Discussion

Let us consider an ULA with array elements L=[10, 20, 50 and 60], let the value of $d = 0.5\lambda$, direction of user is at 0 deg, consider two interference at angles [-20 deg and 20 deg] and let the step size is adaptive. Figure 3 shows the converengence performance of proposed and other LMS algorithms. Figures 4 and 5 show the beamscanning plots of M-LMS1 and M-LMS2 respectively.

From Fig. 3, we notice that, the proposed algorithms are fast in converging the MSE to zero. The M-LMS1 and M-LMS2 algorithms require only 40 and 35 iterations respectively to produce satisfactory output. In Figs. 4 and 5 we notice that the proposed beamformers produced the main beam accurately in the desired direction.

Now let us study the proposed algorithms by varying the number antenna elements. The simulations results for L= 10, 20, 50 and 60 are shown in Figs. 6 and 7. Figure 6 shows the radiation pattern of M-LMS1 and M-LMS2 for small antenna elements (L=10 and L=20) and Fig. 7 shows the radiation pattern of M-LMS1 and M-LMS2 for large antenna elements (L50 and L=60).
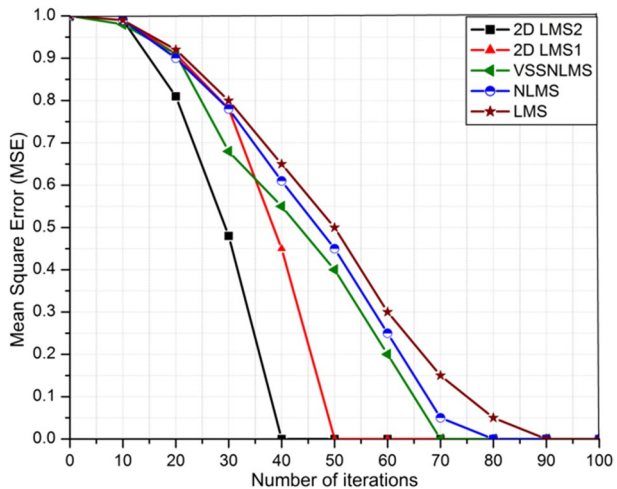

Fig. 3 MSE performance versus No.of iterations

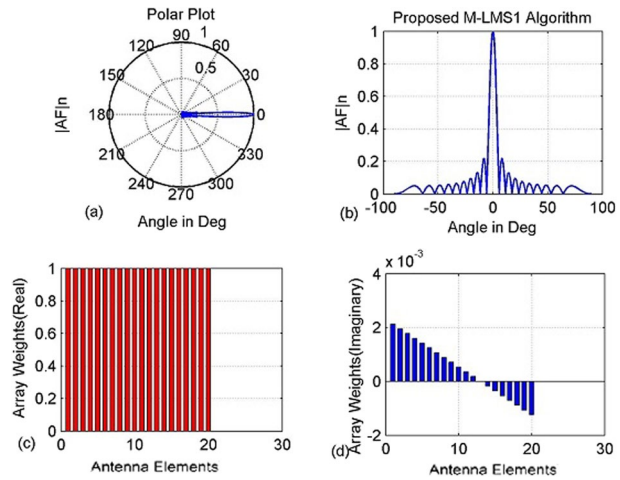**Fig. 4** Beamscanning plot of M-LMS1 algorithm
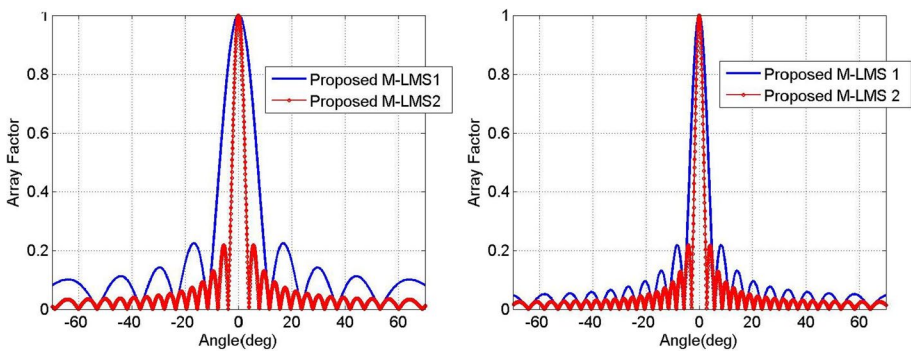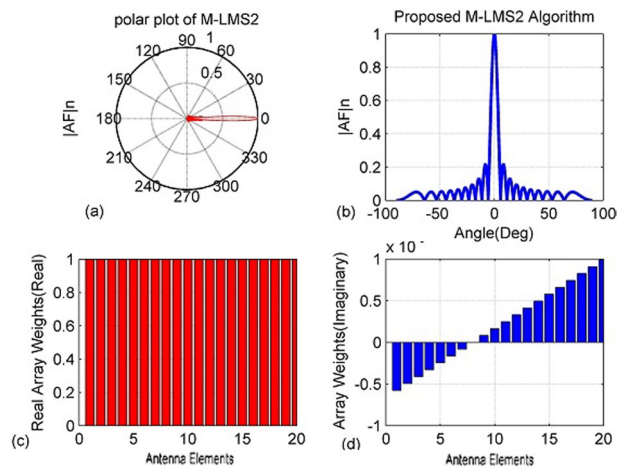

Fig. 5 Beamscanning plot of M-LMS2 algorithm

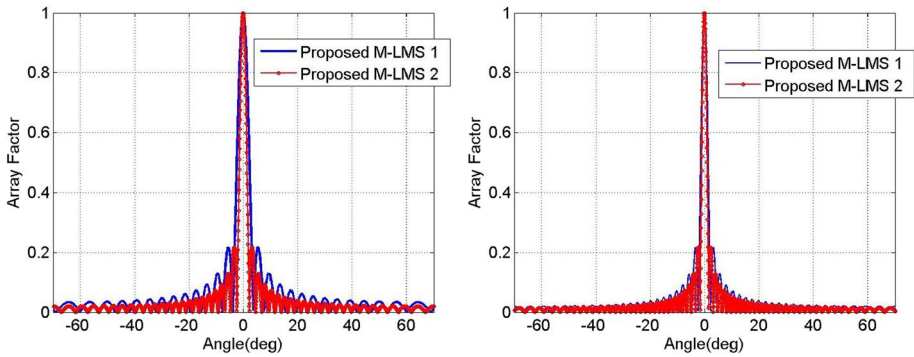**Fig. 6** Radiation pattern of M-LMS1 and M-LMS2 for: **a** L=10 **b** L=20

Fig. 7 Radiation pattern of M-LMS1 and M-LMS2 for: **a** L=50 **b** L=60

3.4 Calculation of Improvement Factor

No. of iterations required for Standard LMS [3] $= I_L = 80$

No. of iterations required for M- LMS1 $= I_{M1} = 50$

No. of iterations required for M-LMS2 $= I_{M2} = 40$

Now, let us compute the improvement factor I_F for both M-LMS1 and M-LMS2 as:

$$I_{F1} = \left(\frac{I_L - I_{M1}}{I_L} \right) \tag{13}$$

$$I_{F1}(in\%) = \left(\frac{I_L - I_{M1}}{I_L} \right) \times 100 \tag{14}$$

$$= \left(\frac{80 - 50}{80} \right) \times 100 = 37.5\% \tag{15}$$

Similarlly,

$$I_{F2} = \left(\frac{I_L - I_{M2}}{I_L} \right) \tag{16}$$

$$I_{F2}(in\%) = \left(\frac{I_L - I_{M2}}{I_L} \right) \times 100 \tag{17}$$

$$= \left(\frac{80 - 50}{80} \right) \times 100 = 50\% \tag{18}$$

Hence, **M-LMS1** and **M-LMS2** show the improvement of about 37.5% and 56% respectively over the standerd LMS algorithm.

From Fig. 6, it can be observed that when L=10 beam width and directivity of M-LMS2 is much better than M-LMS1 algorithm. When this value is increased particularly for L=60 as shown in Fig. 7b, both the methods have almost same beam

width and directivity. Hence the proposed M-LMS2 works well for both small and large antenna arrays and it is much better than M-LMS1.

4 Conclusion

In this work, we developed two modified versions of LMS algorithms to overcome the limitation of the classical LMS beamformer. We name these adaptive beamformers the M-LMS1 and M-LMS2. We devised two new complex adaptive weight update equations for both methods. The convergence plot shows that both methods outperform the classical LMS, the NLMS, and the recent VSSNLMS methods. Both methods are capable of producing the sharp main beams in the required RF signal direction while nullifying the interference. The convergence rates of the LMS1 and LMS2 show 30.75% and 50% improvements over the classical LMS beamformer. Hence, the new LMS1 and LMS2 are more suitable for 5 G and 5GNR and beyond mobile communication for adaptive beamforming.

Declarations

Conflict of interest The author declare that they have no conflict of interest.

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Veerendra Dakulagi Veerendra Dakulagi has earned B.E in Electronics and Communication Engineering and M.Tech. in power electronics from Visvesvaraya Technological University, Belagavi, India, in 2007 and 2011 respectively. He received the Ph.D. degree in array signal processing from the same university in the year 2018. From 2019 to 2021 he was a postdoctoral fellow with the Department of Electrical Engineering, Malaysia. Currently he is working as an Associate Professor in the department of Electronics and Communication Engineering of the Guru Nanak Dev Engineering College, Bidar, Karnataka, India. He has published over 40 technical papers (including IEEE, Elsevier, Springer and Taylor and Francis) and 05 patents in these areas. He is the Editor-in-Chief of the Journal of (1) Advanced Research in Wireless, Mobile and Telecommunication, and the (2) Journal of Advanced Research in Signal Processing and Applications