

RESEARCH ARTICLE | NOVEMBER 10 2025

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AIP Conf. Proc. 3350, 030014 (2025)

<https://doi.org/10.1063/5.0298348>



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Beamforming Array Antenna: New Innovative Research Using Partial Update Adaptive Algorithms

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Abstract: The key innovation and contribution of this research was to apply Partial Update (PU) for Beamforming Array Antennas (BAA) instead of using full band adaptive algorithms, as no previous attempt had been made to do so. A subset of the array's elements, instead of all of them, will be connected to by PU methods. This enables the system to decrease the number of active antennas throughout all cells, while maintaining high performance and low-cost value. In this research, we present a new BAA's architectural method for decreasing the number of base station antennas by controlling and minimizing the number of phase shifters. The methods for Partial Update Least Mean Square (PU LMS), such as sequential PU, M-max PU, periodic PU, and stochastic PU, will be the focus of this article. Results from simulations with a Uniform Linear Array (ULA) show that the M-max, periodic, and stochastic methods carry out similarly to the full-band LMS algorithm (except sequential PU method), in terms of mean square error, tracking weight coefficients, and estimation error signal, all even as having a quick convergence time, and a low level of mistakes sign at steady-state error. Additionally, the PU algorithms preserve the radiation-patterns styles, minimum distortion, and symmetrical characteristics, which have a massive impact on wi-fi conversation systems. While completely adaptive arrays are effective in suppressing interference signals through null steering, the new BAA's architectural approach has significant advantages. The suggested array successfully generates deep nulls with very fast convergence time, as demonstrated by the simulation results.

Keywords: Partial Update Adaptive Algorithm, Array Beamforming, M-Max PU , Full band LMS, Periodic PU , Sequential PU, and Stochastic PU methods.

INTRODUCTION

In order to boost spectral efficiency, energy savings, and performance in the face of interference from a limited spectrum, next-generation cellular communication networks use a large number of antennas. BAA is one such antenna design that makes this possible. Future wireless communication systems, including 5G, are expected to rely heavily on BAA technology. Adaptive array beamforming aims to improve the wireless mobile link and system performance by ensuring that signals at BSs and mobile stations are correctly regulated. By efficiently reducing multipath fading and channel interference, the antenna increases the capacity of wireless communication networks. Beamforming (BF) methods allow signals to be concentrated in a certain direction and shaped to fit the surrounding environment.

Phased Array Antennas (PAA), constitute the most regular, and sustainable BF technique.[15]. PAAs are arrays of antenna elements, driven by indicators, with well-defined phase relationships, among the ones additives. N section shifters, or other lively manage units were wanted for the ULA's N antenna elements.

Very few articles [1-9] describe algorithms or methods for decreasing the number of ULA elements and, by extension, phase shifters. By using this technique, we can lessen the overall number of active antennas in every cell, which results in significant cost savings and increased energy efficiency. The number of energetic antenna elements, inside the cell relative to the power budget, allocated to each BS is the primary component in determining the cell's electricity performance. Cascaded perspective offset phased array antennas (CAO-PAAs), and dimensionality reduced CAO-PAAs (DRCAO-PAAs) have been supplied as new ideas in [1].

With the help of a coefficient matrix, they were able to depict the phase shift steering in any direction. After that, we reduce the number of phase shifters to bring the dimensionality of the coefficient matrix down [1]. Other methods, such as reduced active controller-based vector synthesis, have also been proposed to cut down on the number of active antennas [2-8]. Sub-array compression is another approach; in this case, a unique phase shifter is used For every sub-array. The writer of [9] proposed connecting an adaptive algorithm (like LMS, RLS, CG, or CMA), to handiest a small number of the array elements, placed inside the middle of the array, in place of all factors, leaving the other elements unaffected via the version procedure due to the fact they've less of an impact at the sample of the array.

Although the PU algorithms have received much attention in the past several years (both theoretically and in practice; see [10,23]), they have not yet been implemented in array BF systems.

To the best of our knowledge, adaptive PU approaches have never been applied in a study including BAA. This research proposes a new architecture system model for applying PU approaches for BAA, which is seen as the paper's key innovation because it allows for a reduction in the total number of antennas. Partial update adaptive approaches only link up with a fraction of the available antenna elements. Then, PU LMS methods will be utilized, including sequential PU, M-max PU, periodic PU, and stochastic PU methods. Therefore, the performance of these techniques will be on par with that of full band adaptive arrays In phrases of convergence time and capability to suppress interference alerts thru null steering. The LTE channel model type Extended Typical Urban (ETU), which accounts for multipath fading, will be utilized in the proposed model to assess its efficacy.

This paper's reminder will be as follows: The BAA signal model will be introduced in the following section, while the remaining sections will include BF theory based on Partial Update adaptive algorithms, the suggested model's architecture, simulation results, and conclusions.

SIGNAL MODEL FOR BF ARRAYS

Next-generation networks cannot be built without mobile carriers adopting the use of BF antennas. In contrast to older antennas, that were limited to broadcasting, and receiving on fixed radiation patterns, BF antennas can dynamically adjust the directions of their main, and null beams according to the location of their linked users. This is why people commonly refer to these innovative antennas of the future as "beamformers." BF antennas are notable for their ability to successfully decrease interference, which in turn considerably improves The signal to interference, and noise ratio (SINR), and the user revel in.

Transmit BF tries to increase capacity By way of reducing signal interference from other users, and increasing the obtained signal electricity for every user. The goal of the BF procedure, is to construct the radiated beam patterns of an antenna, by fully generating the processed signals towards the designated terminals, and nullifying the beams of interfering signals.

ULA has emerged Because the method of desire, for research research within the discipline of array sign processing, due to the fact that, it is so simple to implement. Figure 1 shows an N-element ULA. Assume the separation (in wavelength units) between the individual elements of the antenna is denoted as d : $d = 0.5 \lambda$, where λ denotes, the wavelength of incoming signals. This diagram, illustrates the modification of the weight vector $\mathbf{w} = [w_1 \ w_2 \ \dots \ w_N]^T$, to minimize errors during the iterative adjustment, of the array weights [24]. The signal $s(n)$, and the interferences $i_1(n), i_2(n), \dots, i_N(n)$, are received by a set of N elements, each of which has N ability weights. Every signal received at element m, also contains a little amount of additive Gaussian noise. Time is represented by each of the n samples of time.

THE LMS BF METHOD

Wireless communication applications frequently employ the straightforward LMS BF technique. As a result, several applications use this technology as an adaptive BF technique. The output of the weighted array is written as [24].

$$y(n) = \mathbf{w}^H(n) \mathbf{x}(n) \quad 1)$$

were:

$$\begin{aligned} \mathbf{x}(n) &= a_0 \mathbf{s}(n) + [a_1 \ a_2 \ \dots \ a_N] \cdot \begin{bmatrix} i_1(n) \\ i_2(n) \\ \vdots \\ i_N(n) \end{bmatrix} + z(n) \\ &= \mathbf{x}_s(n) + \mathbf{x}_i(n) + z(n) = \text{input signal} \end{aligned} \quad 2)$$

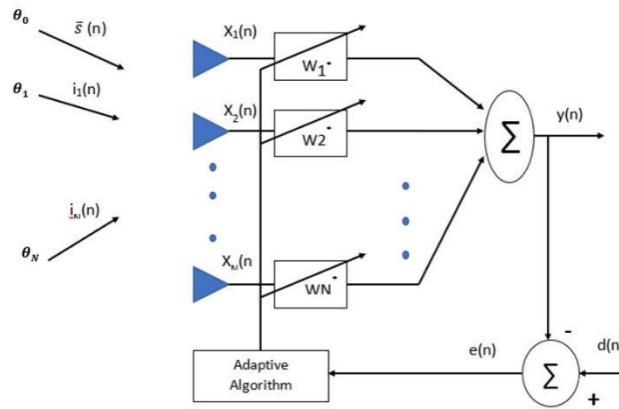


FIGURE 1. Adaptive Array BF System

With :

$\mathbf{w} = [w_1 \ w_2 \ \dots \ w_N]^T$ = array weights

$\mathbf{x}_s(n)$ = desired signal vector

$\mathbf{x}_i(n)$ = interfere signals vector

$z(n)$ = Gaussian noise with a zero mean for each channel

\mathbf{a} = steering vector for θ_i , direction of arrival using an N-element array

The distinction between the preferred signal $d(n)$ and the actual output sign $y(n)$ (eq (1)) known as error sign $e(n)$, as defined below [1]).

$$e(n) = d(n) - \mathbf{w}^H(n) \mathbf{x}(n) \quad 3)$$

The weight vector of LMS is received, via the use of the gradient of the cost function [1]:

$$\mathbf{w} = \mathbf{w}(n) + \mu e(n) \mathbf{x}(n) \quad 4.1)$$

If update vector $\mathbf{f}(n) = \mu e(n) \mathbf{x}(n)$, then

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{f}(n) \quad 4.2)$$

Parameter step-size (μ) has a direct impact on the convergence of the LMS method, as shown by equation (4.1).

PARTIAL UPDATE (PU) METHODS

Partial updates (PU) are a method used to decrease processing time required during the adaptive filter update phase. There has been a lot of attention paid to these algorithms recently [22] from both consumers and academics. The partial-update method, as opposed to fully Updating all $N-1$ coefficients, exclusively updates the $M \times 1$ coefficients, Where M , is less than N . This study discusses fundamental methods for partial updates.

These methods include Periodic, Sequential, Stochastic, and M-max PU. Each PU algorithm under investigation here can be summarized by a single update equation [22]:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \mathbf{I}_M(n) e(n) \mathbf{x}(n) \quad (5)$$

The sole difference between PU methods (5), and the full update LMS algorithm (4.1), is the weight selection matrix $\mathbf{I}_M(n)$. The formula is as follows, [25]:

$$\mathbf{I}_M(n) = \begin{bmatrix} i_0(n) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & i_{L-1}(n) \end{bmatrix}, \quad i_k(n) \in \{0,1\}, \quad \sum_{k=0}^{L-1} i_k(n) = M \quad (6)$$

Thus, the weight selection matrix is a diagonal matrix comprising entries, of 0 or 1, where M denotes the sum of the entries valued at 1, inside the matrix, indicating which M coefficients are to be updated at generation n , while the diagonal of the matrix incorporates $N-M$ zeros.

The selection matrix is also accompanied by the number M , which denotes the quantity of adaptive filter out weights, chosen for updating at every sampling c programming periodic. In each subsequent sample interval, we toggle the values of the diagonal elements within the desire matrix to either 0 or 1 [25].

$$i_k(n) = \begin{cases} 1 & \text{if } k \in \mathcal{J}_M(n) \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Wherein the array of M filter, out weight indices, denoted through $\mathcal{J}_M(n)$, represents the adjustments to the coefficients for the n th iteration. According to [25], the specific PU LMS algorithm used to define this set can change.

Partial updates, like in (5), provide the main benefit of reducing complexity to work around complexity limitations in hardware. One potential downside of partial updates is their potentially slower convergence speed. In this case, it's possible to think of partial updates as a compromise between computational complexity, and convergence rate.

PU Sequential Method

By only updating a subset of the adaptive filter coefficients, with every iteration (n), Sequential PU significantly decreases the computing load required for adaptation. The sequential PU method iteratively adjusts a fraction of the coefficient vector with each iteration until it satisfies the complexity constraints [25]. In this way, the adaptive filter coefficient vector is "decimated" by using the application of successive PU.

The subsets of coefficients to be up to date are selected in a deterministic spherical-robin method. This results in periodic updates independent of the input signal. Following is the formula for computing the coefficient selection matrix $\mathbf{I}_M(n)$:

The value of $\mathbf{I}_M(n)$ for a given N and M is left unstated. Think about the M different subgroups of the set of coefficient indices, (This is, subsets with M participants) $S = \{1,2,3,\dots,N\}$, denoted by, I_1, I_2, \dots, I_C where $C = \binom{N}{M}$. The symbol S is the period of coefficient updates.

Let's assume that $B = N/M$ is a whole number. Then, any B M -subsets of S can be used to implement the sequential partial update approach. In order to simplify the adaptation process, an adaptive filter of length N can have its M coefficients updated at each iteration. There are several problems with the method as a result [10, 11], including a poor convergence rate and instability for cyclostationary input signals.

PU M-max Method

As an input, M-max LMS selects the M elements from $\mathbf{x}(n)$, that significantly affect the filter weights. If the generic adaptive filter from equation (5) is applied to a subset of the data, the result is:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{I}_M(n) \mathbf{f}(n) \quad (8)$$

Where $\mathbf{f}(n)$ is update vector

$$\mathbf{f}(n) = [f_1(n), f_2(n), \dots, f_N(n)]^T \quad (9)$$

The coefficient selection matrix $\mathbf{I}_M(n)$, given in (6), has the values [25]: for its diagonal.

$$i_k(n) = \begin{cases} 1 & \text{if } |\mathbf{f}_k(n)| \in \max_{0 \leq l \leq N} (|\mathbf{f}_l(n)|, M) \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where the set of M maximum values for the elements f_l is represented by $\max_{0 \leq l \leq N} (\mathbf{f}_l, M)$ [25]. Both M-max updates and sequential partial updates 'decimate' the update vector in the same way.

PU Periodic Method

When periodic Partial updates are implemented to the adaptive filter coefficients in (4.2), the results are as follows:

$$\mathbf{w}((n+1)S) = \mathbf{w}(nS) + \mathbf{f}(nS) \quad , \quad n = 0, 1, 2, 3, \dots \quad (11)$$

$$\mathbf{w}(ns + i) = \mathbf{w}(nS) \quad , \quad i = 0, 1, \dots, S-1 \quad (12)$$

The coefficient updates of $\mathbf{w}(n)$ are reduced by a factor of S by the periodic PU approach. The coefficients of the adaptive filter clear out are retained consistent between updates, i.e., $\mathbf{w}(nS) = \mathbf{w}(nS+1) = \dots = \mathbf{w}(nS+S-1)$.

At each iteration S^{th} , where k equal to $0, S, 2S, 3S, \dots$, the adaptive filter's coefficients are updated.

Due to the reduction of updates by S , the adaptation process, can calculate the replace vector in S iterations (n). As a result, each iteration's normal processing requirements are decreased by S [25].

PU Stochastic Method

The stochastic method may be carried out, with the aid of a non-deterministic variation of the sequential approach [11], in which the coefficient of adaptive clear out subsets is chosen, at random in place of earlier. The subsequent coefficient selection matrix is employed in the stochastic PU approach:

$$\mathbf{I}_M(n) = \begin{bmatrix} i_0(n) & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & i_N(n) \end{bmatrix} \quad , \quad i_k(n) = \begin{cases} 1 & \text{if } k \in \mathcal{J}_{m(n)} \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

where $m(n)$ is an independent random process. If the overheads for producing the random signal $m(k)$, are discarded, stochastic PU approaches can achieve complexity reductions comparable to those realized by sequential PU [25]. In addition, the stochastic partial update algorithm performs better in terms of network speed than the sequential partial update method [18].

Design Principles for the New Model

The massive number of antennas utilized in 5G networks' precoders and detectors makes adaptive array BF an absolute necessity [26]. Because BAA consume less energy to convey signals to their target user, next-generation networks can reduce their overall power consumption and amplification costs.

Reduced overall energy consumption and cost could be achieved by using A commonplace variety of useful antennas, for all of the gadget's cells. Energy efficiency for each BS's prescribed power consumption is significantly affected by the cell's total number of operational antenna components.

Adaptive array BF is primarily achieved through PAAs, which consist of arrays of antenna elements regulated, by signals exhibiting precise phase relationships among those elements [26]. In most cases, N phase shifters, or other active manage components are needed for a phased array antenna. There are numerous suggestions, that have been put forward with the intention of reducing the requirement for phase shifters; however, these initiatives can be unsuccessful until extra energetic manipulate gadgets are carried out.

There have been several studies of these difficulties at ULA, but this is the first time anyone has tried using update partial (PU) adaptive filtering. The architecture that has been proposed employs update partial adaptive filtering, as demonstrated in Figure 2, in order to selectively increase or decrease the wide variety of antennas (M) for each ULA detail, ensuring that M is less than N .

In accordance with this approach of selecting, only M of the N coefficients will be altered with each update at the most. So that all of the adaptive filter coefficients can be updated over the course of time, the selected M coefficients should vary between iterations, at least in theory. This has significant ramifications, including a smaller antenna array in terms of both size and weight, and a a Radio Frequency (RF) chain, that is shorter, for each character antenna detail.

Streamlining Signal processing, and reducing the quantity of storage area required are each vital issues, as the number of indicators received decreases. Therefore, the total gadget value is reduced.

However, the technique of lowering the range of antenna elements in antenna arrays, while keeping semi-similar radiation pattern houses to the entire band has a primary effect on wireless communique systems. The radiation sample is almost distortion-loose, and flawlessly symmetric throughout all array planes, while the range of elements is kept small.

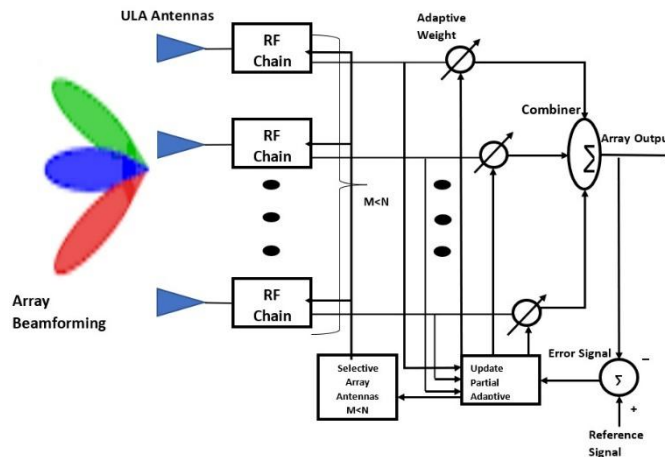


FIGURE 2. The proposed model's architecture

Simulation Outcomes

As shown in Figure 2, the array BF base station is made up of a homogeneous linear antenna array that is comprised of eight receiving antennas that are separated by a half wavelength. The supposed user's elevation perspective is 0° , and the other users' elevation angles are 20° , and -30° respectively. In total, 400 iterations have

been performed. An essential layout parameter is the range of filters taps, that need to be updated at every sample interval. In a PU-LMS algorithm, M out of N adaptive filter coefficients are updated with each iteration, with the chosen M coefficients values beginning at half the filter taps. This can reduce the processing power required to update the filter by a factor of two, and at worst, it can reduce it to a factor of one [22]. Therefore, the optimal value for the PU algorithms' M parameter is 5. The step size was determined automatically within the MATLAB software according to (14), thus it was the same for all methods examined in this section. It was shown that this criterion for selection would yield results that were almost identical to those obtained using the full band LMS method. The most eigenvalue λ_{max} , of the anticipated enter correlation matrix \hat{R}_{xx} , is utilized in formula (14) [24]:

$$0 \leq \mu \leq \frac{1}{2\lambda_{max}} \quad (14)$$

The following are the instantaneous approximations of \hat{R}_{xx} :

$$\hat{R}_{xx}(n) \approx \mathbf{x}(n) \mathbf{x}^H(n) \quad (15)$$

In accordance with 3GPP, we used the LTE channel model type ETU, to replicate urban environments, with huge cells, and massive postpone spread conditions [14], and to account for multipath fading propagation [28,29]. This channel version has 9 special paths, each with a gain of, [-1, -1, -1, 0, 0, 0, -3, -5, -7], and a corresponding delay of [0, 50, 120, 200, 230, 500, 1600, 2300, 5000] * 10^{-9} / T_s [28,29].

Mean square Error (MSE) performance (in dB), of each technique is displayed one after the other, in Figure 3, then, they are grouped in one determine, as proven in Figure 4. These Figures display that, the M-max, Periodic, and Stochastic PU strategies perform similarly to their corresponding full band LMS, opposite numbers concerning the convergence charge, and minimal blunders level within the constant-country area. Alternatively, Sequential PU LMS algorithm performance has been negative because of gradual convergence charges, and large steady state mistakes.

The main reasons of this bad performance due to it needs a large number of iterations (more than 400) and relied on trial and error to get the optimal value for the step size parameter (μ). Figures 5 display the estimation tracking weight coefficients for all methods. Figure 6 and Figure 7, illustrated the estimation output sinewave signal in separate figures and grouped in one figure respectively. We see the estimated output signal as it is produced. Based on these figures, it can be seen that the M-max, Periodic, and Stochastic PU methods all produce reliable estimates; however, the sequential PU method's accuracy drops.

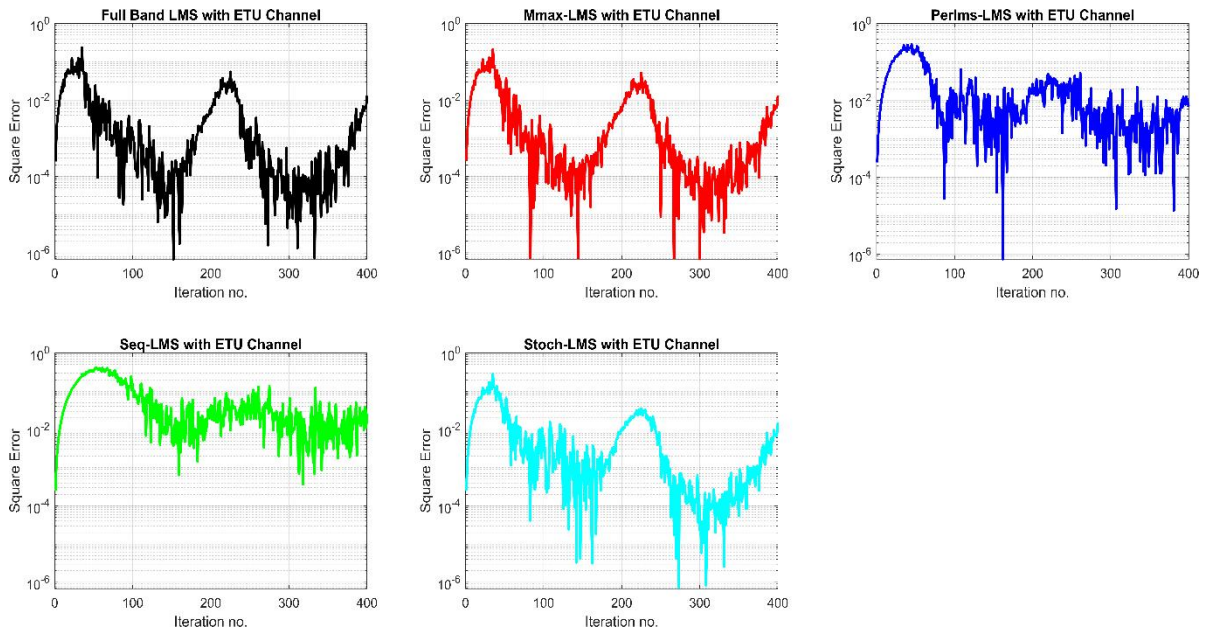


FIGURE 3. Square error performance (in dB) organized separately for each method

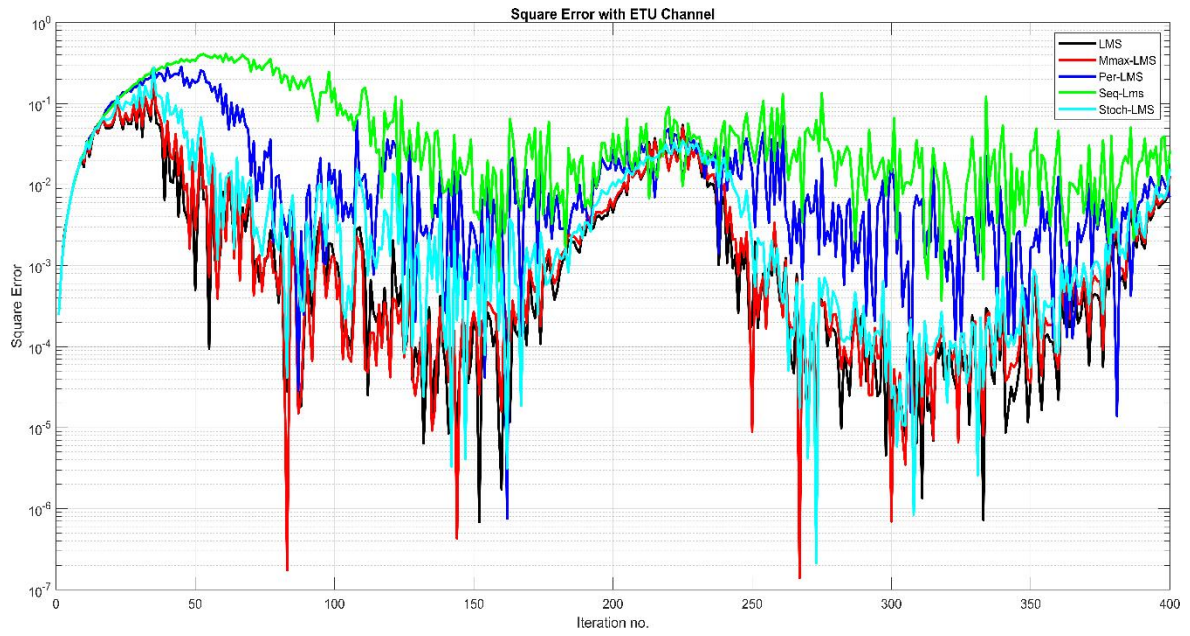


FIGURE 4. Square error curves organized into one figure for all methods

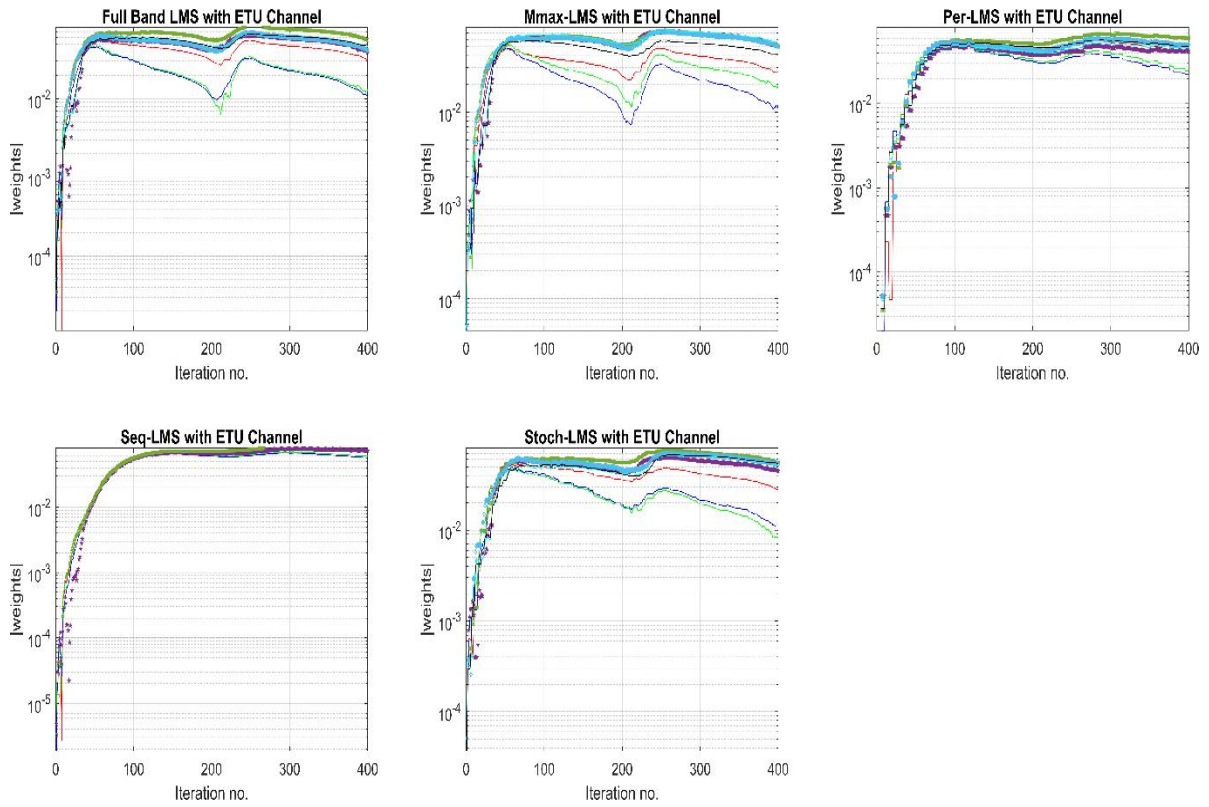


FIGURE 5. Weight coefficients tracking for all methods

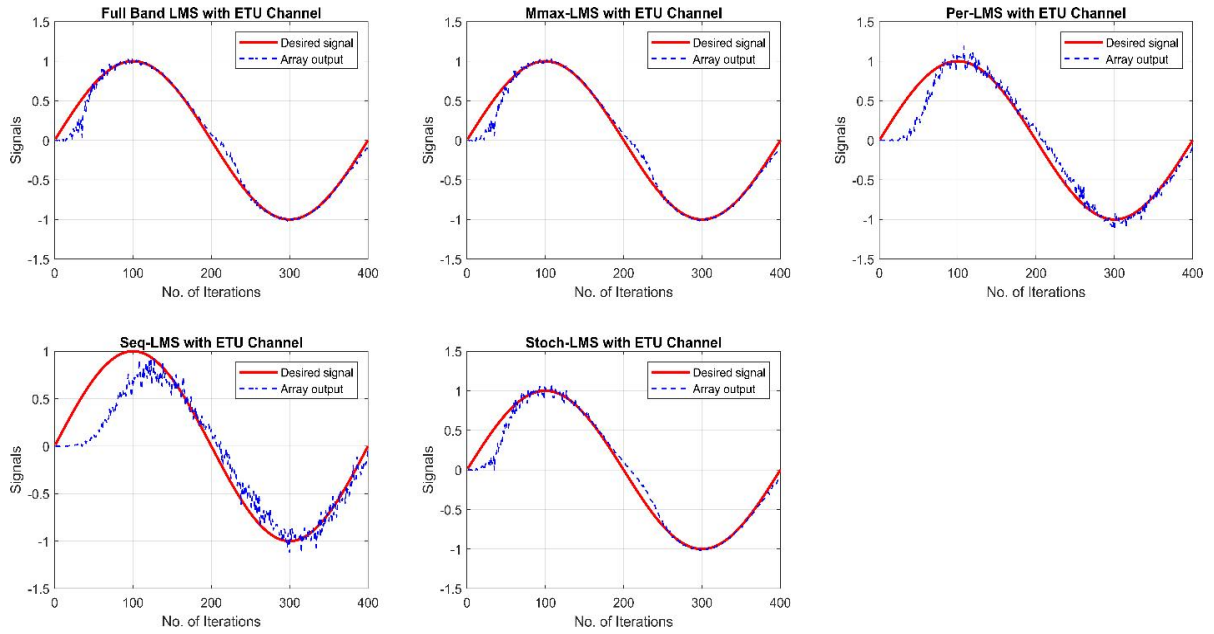


FIGURE 6. Estimation output sinewave signal organized separately for each method

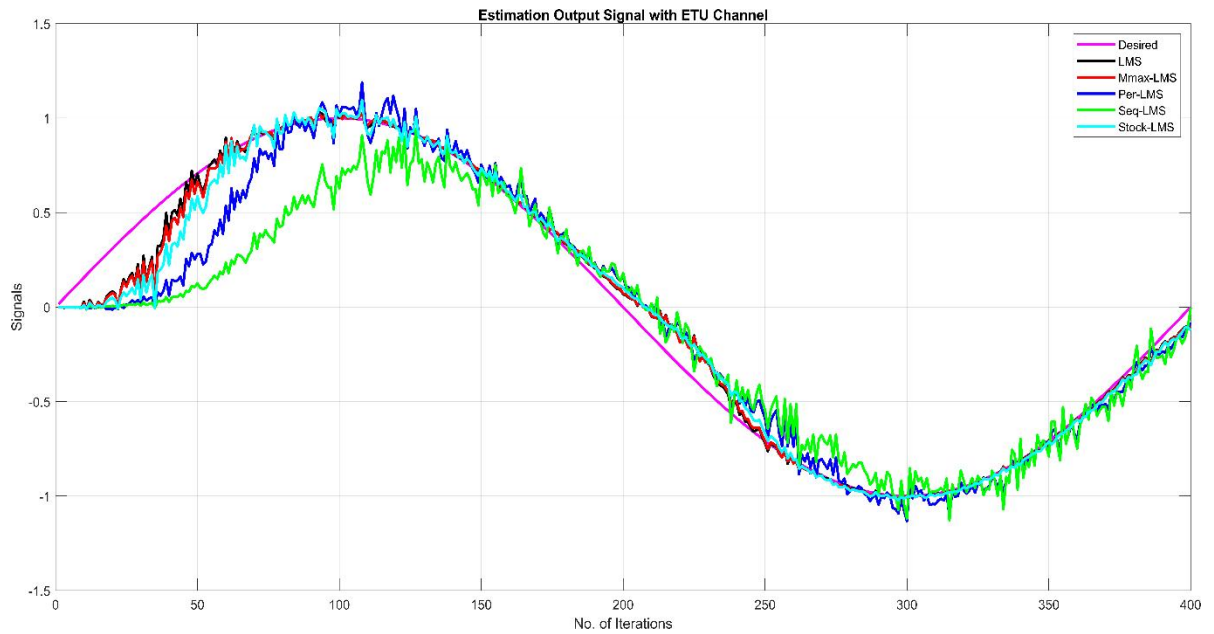


FIGURE 7. Estimation output sinewave signal organized into one figure for each method

Figure 8 displays the polar plot pattern for all methods. The configuration and algorithm used to determine how the polar sample is dynamically modified, to in shape the present-day sign environment. There is no radiation within the foremost lobe of this pattern, and there are nulls from each angle. A concentrated laser beam is accessible from the PU LMS algorithms. It may be applied to decorate reception or to attenuate noise. Figure 9 depicts the radiation

array styles, for the entire band LMS, employing N equals eight elements, and the PU LMS algorithms, using M equals 5 elements; the full band LMS accommodates a complete of 8 elements. The array configuration of PU LMS algorithms, with the exception of the sequential variation, bears some resemblance, to that of full band LMS. This permits the number one beam to be directed, toward the intended orientation at the same time, as simultaneously nullifying it within the course of interference.

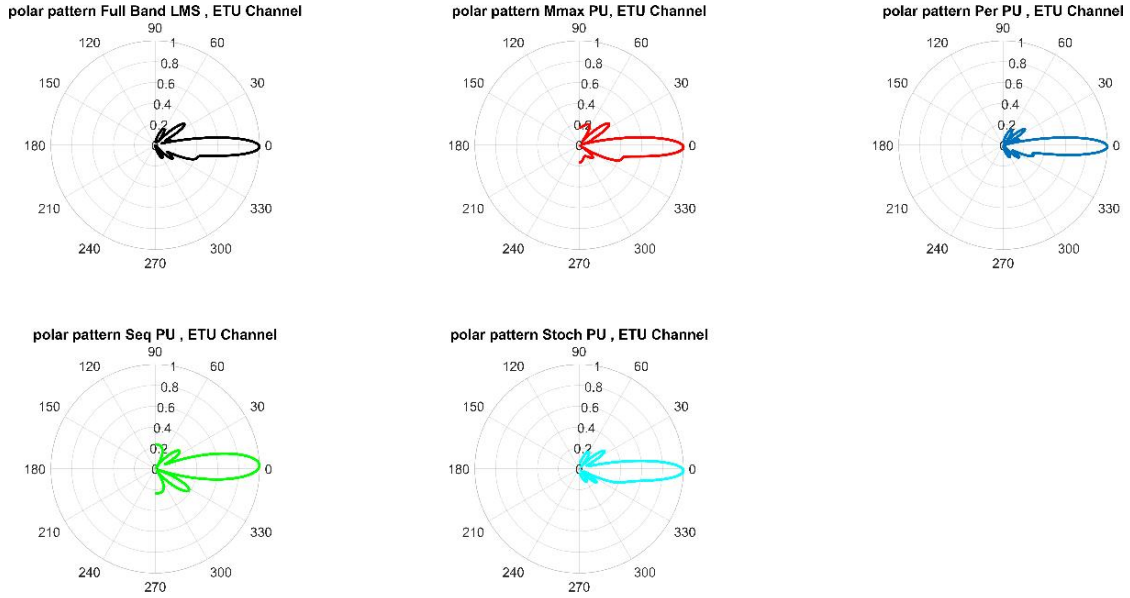


FIGURE 8. Polar plot pattern for all methods

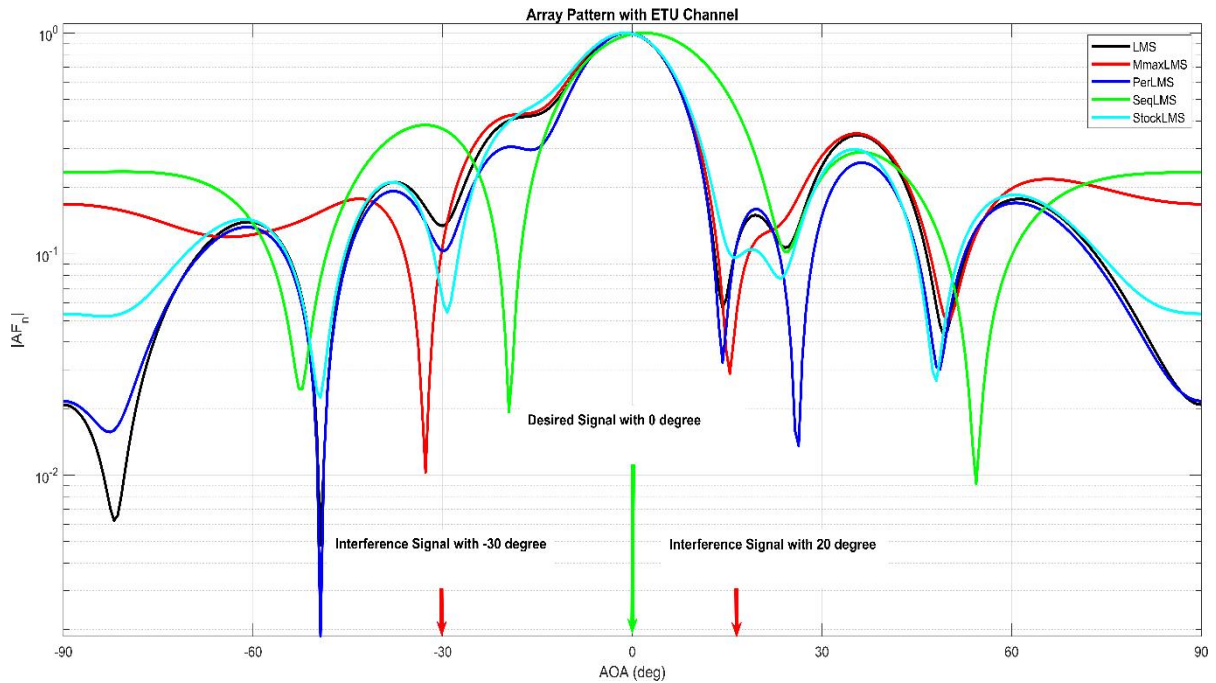


FIGURE 9. Array pattern for all methods

To place the necessary nulls, the suggested array architecture uses only 5 configurable elements, making it comparable with the overall band LMS set of rules. With regard to the geometry of the main beam, the PU LMS algorithms that have been proposed additionally come very close to achieving the best uniform array pattern.

CONCLUSION

Although many methods have been presented for lowering the number of antennas required for array BF, no one has yet tried to implement Partial Update adaptive filtering. This is because of the need to lessen the size, weight, and complexity of the associated radio frequency (RF) chain, as well as the feeding network in adaptive antenna arrays. This article's primary contribution is that it changed, into the primary to try using PU adaptive methods, for selecting or choosing the number of antennas (M) with the aid of deciding on or deselecting the RF chain for every detail in the ULA so that M is less than N, thereby decreasing the number of active components. This results in a more compact and lightweight antenna array system with a condensed RF chain for every antenna detail. We need to speed signal processing and decrease the quantity of garbage wished because fewer alerts are being obtained. This results in savings for the system as a whole. The results of the simulation show that, with the exception of Sequential PU LMS, the performance of PU LMS algorithms is comparable to that of the overall band LMS method, in terms of the amount of time it takes for the algorithm to converge, and the amount of minimum blunders that it produces in regular state. In wireless communication systems, the PU algorithms ensure that the beneficial effects are preserved by utilizing radiation patterns that have low distortion and symmetrical characteristics.

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