Interference Mitigation in the Wireless Communication Systems Using Adaptive Filters

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Abstract. In the current fifth generation (5G) wireless communication systems, the interference mitigation issue becomes a major and most important task for improving the performance of such systems due to corded spectrum and increased demands for new applications. Antenna arrays controlled by adaptive algorithms are proved to be a good solution for such problem. However, there are still some practical limitations in implementing such fully adaptive arrays especially when consisting a large number of the controllable elements. Other disadvantages of such arrays include long convergence time of the algorithm and the complexity of the beamforming network. In this paper, an adaptive algorithm is connected to only limited number of the array elements instead of all elements. We found that the elements that located on the center of the array could be chosen as adaptive, while the other elements which have less effect on the array pattern are left without adaptation process. Thus, the proposed array has many advantages with compared to those of the fully adaptive arrays while maintaining the same performance in suppressing the interference signals through null steering. Simulation results show that the effectiveness of the proposed array in generating deep nulls with very short convergence time.

Index Terms — Rectangular Arrays, Partially Optimized Elements, Constraint Optimization.

1. Introduction

The performance of the wireless communication systems can be significantly reduced under highly interference environment due to the crowded spectrum. This situation is expected to become worse in the near future when emerging the fifth generation (5G) wireless communication systems [1-2]. One of the simplest and oldest method for noise suppression is by using median filters [3] for image restoration. Other advanced methods use adaptive filters to control the complex weights of the array elements whose reshape the corresponding array patterns according to the required radiation characteristics such as steered nulls toward undesired direction and maintaining the main beam undistorted [4].

In some simple scenarios, the interfering signals may originate from fixed directions, thus, the array weights won’t need to be adaptive or controllable. However, the uncontrollable array elements become useless under the conditions of rapidly changing interfering directions. In this case, it is necessary to use an adaptive algorithm to keep updating and recalculating of the optimum array weights and accordingly the corresponding array pattern must allow for the continuous adaptation to any changing in the electromagnetic environment (i.e., pointing the main beam of the array pattern toward desired signal and the nulls in the direction of undesired interfering signals) [5-9]. The adaptive variables (controllable elements) are different from fixed weights (uncontrollable elements) where it allows for continuously updated [10-12].

In this paper, the pros and cons of the adaptation process of the adaptive weights under various optimization algorithms such as conjugate gradient (CG), least mean squares (LMS), sample matrix inversion (SMI), recursive least squares (RLS) and the constant modulus algorithm (CMA) are investigated and compared. Then, these adaptive algorithms are applied only to the limited number of
array elements instead of all elements. Thus, not all of the array elements are adaptive. Indeed, there are many elements are nonadaptive or fixed. Therefore, the beamforming network is not too complex and the algorithm may converge very fast. It is worthy to mention that the use of only few elements for null steering have been previously presented in [13]. However, the concept of the controllable elements by means of adaptive algorithms is new and worthy to be investigated due to many advantages and applications.

2. Optimization Algorithms for Adaptive Arrays

Figure 1 shows the block diagram of the popular adaptive array system where it consists two major parts, namely, adaptive controller, and the controllable complex-weights, i.e., amplitude and phase excitation of each array elements. These complex weights are controlled by the adaptive controller via an optimization algorithm. The criteria of the optimization algorithm could be minimizing the means square error (MSE), maximizing the signal to interference ratio, shaping the array pattern by steering the main beam toward desired signal and nulls toward interfering directions, and minimizing the variance. In this section, the nulling capability for interference suppression of different adaptive algorithms is examined under full control of all array elements.

\[ \mathbf{w}(k+1) = \mathbf{w}(k) + \mu e^*(k) \mathbf{x}(k) \]  

Where \( \mathbf{w} = [w_1, w_2, ..., w_N]^T \) are the complex weights, \( \mu \) is the step size of the algorithm, and \( \mathbf{x}(k) \) is the input signals including the desired signal, \( s(k) \), interfering signals, \( i_1(k), i_2(k), ..., i_I(k) \), \( I \) is the total number of the interfering signals, and the Gaussian noise signal, \( n(k) \).
\[ \bar{x}(k) = \bar{a}_0 \bar{s}(k) + [\bar{a}_1 \bar{a}_2 \ldots \bar{a}_I]^T + \bar{n}(k) \]  
\[ (2) \]

In the vector form, it can be written as

\[ \bar{x}(k) = \bar{x}_s(k) + \bar{x}_i(k) + \bar{n}(k) \]

\[ (3) \]

Where \( \bar{a}_0 \) is the desired steering vector, and \( \bar{a}_1 \bar{a}_2 \ldots \bar{a}_I \) are interfering steering vectors. From Figure 1, the error signal can be written as

\[ e(k) = d(k) - \bar{w}^H(k) \bar{x}(k) \]

\[ (4) \]

As mentioned, the main concern in this paper is to adaptively shape the array pattern to place the required nulls. The array factor (AF) can be found by

\[ \text{AF}(\theta) = \sum_{n=1}^{N} w_n^H e^{j(n-1)\frac{2\pi}{\lambda} \sin(\theta)} \]

\[ (5) \]

The above-mentioned equations are simulated and the converged LMS array pattern is shown in Figure 2. For comparison, the array pattern of the uniformly excited (i.e., all the weights’ value are unity) linear array is also shown in Figure 2. In this example, one desired signal impinging on the array from direction \(-40^\circ\), and two interfering signals from directions \(-5^\circ\) and \(-26^\circ\), respectively is considered. The number of array elements is \( N=12 \) (Note that all of these array elements are considered here to be controllable). The step size value is chosen to be \( \mu = 0.006 \) which is within the acceptable range according to [14] and ensures that the LMS algorithm perform well. It can be seen that the LMS array pattern accurately placed the required nulls. However, the number of the controllable elements, \( N=12 \), is much larger than the number of the interfering signals, \( I=2 \). This may add unnecessary complexity to the feeding network.

\[ \text{Figure 2. LMS array pattern for fully controllable array elements.} \]

2.2 Conjugate Gradient (CG)

The LMS algorithm uses the steepest descent method to converge to the optimum weight values. However, this process needs to pass through many iterations before get converged. Thus, it is generally classified as a slow algorithm which is undesirable in the applications that require fast tracking capability [8].

The convergence speed can be improved by the use of conjugate gradient method instead of steepest descent method and thus the algorithm is referred to as conjugate gradient (CG) [16]. In CG, the array weights are updated iteratively such that the new paths are perpendicular to the old paths. The updating process of the controllable weight vector is [16, 17]:

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\[ \text{Figure 2. LMS array pattern for fully controllable array elements.} \]
\[ w(k + 1) = \bar{w}(k) - \mu(k) \bar{D}(k) \]  \hspace{1cm} (6)

Where \( \bar{D}(k) \) is the direction vector which gives the new perpendicular paths during the updating process, and \( \mu(k) \) is the variable step size which can be found according to [9]. The array pattern based on CG algorithm is shown in Figure 3. The desired and interfering directions are same as in the previous example. Also, the number of array elements is chosen to be \( N=12 \) where all of them are controllable. Their optimum values after CG convergence are 

\[
\begin{align*}
    w_1 &= 0.7448 - j0.6673, \\
    w_2 &= 0.4549 + j2.8912, \\
    w_3 &= -2.8671 - j2.2878, \\
    w_4 &= 3.3819 - j0.0546, \\
    w_5 &= -2.5254 + j0.7198, \\
    w_6 &= -0.5865 + j2.4628, \\
    w_7 &= -3.0749 - j1.2352, \\
    w_8 &= 3.2749 - j2.8870, \\
    w_9 &= 1.1888 + j2.6427, \\
    w_{10} &= -3.8234 - j0.1385.
\end{align*}
\]

As can be seen, the desired nulls in the CG array pattern are accurately placed. However, this result cannot be released in practice due to unavailability of RF components to release such accurate weight values.

2.3 Recursive Least Squares (RLS)

Another way to accelerate the convergence speed of the adaptive controller that shown in Figure 1 is by applying recursive least squares (RLS) algorithm instead of LMS. For exponentially weighted RLS, the update error and weight equation are [15, 17]

\[
\begin{align*}
    e(k + 1) &= d(k + 1) - \bar{X}^T(k + 1)\bar{w}(k) \\
    \bar{w}(k + 1) &= \bar{w}(k) + \phi^{-1}(k + 1)\bar{x}(K + 1)e(k + 1)
\end{align*}
\]  \hspace{1cm} (7) \hspace{1cm} (8)

where \( \phi^{-1}(k) \) is the inverse correlation matrix \( \phi(k) = \bar{X}^T(k)\bar{X}(k) \). Note that instead of doing an update in the direction of the input vector \( \bar{X}(k) \) as in the LMS algorithm, the input signal is first whitened by multiplied it by the inverse correlation matrix. More details about RLS algorithm and its derivation could be found in [14] and [16]. The array pattern based on RLS algorithm is shown in Figure 4. Even though the algorithm is converging fast, its nulling capability for interference suppression is unsatisfactory.

2.4 Constant Modulus (CM)

In this algorithm, the desired signal should ideally have a constant magnitude. However, some difficulties in maintaining the signal’s amplitude constant arise in the multipath fading channels. Also, the frequency selective channels destroy the constant magnitude of the signal. Generally, to keep the constant modulus property an amplitude equalizer should be used to restore the amplitude of the original signal.

The error signal in CM algorithm can be written by [18]
Where $P$ is chosen to be 1. This error signal can replace the previous error signal that was shown in Figure 1 and equation (4). The updating process of the controllable weight vector of this algorithm remains same as that of the LMS algorithm. The only difference between CM and LMS is the error signal.

The array pattern based on the CM algorithm is shown in Figure 5. Like other examples, a desired signal from direction $-40^\circ$, and two interfering signals from directions $-5^\circ$ and $-26^\circ$, are assumed to impinge on an array with $N=12$ controllable elements. From this figure, it can be seen that the required nulls are not accurate enough and thus the interfering signals cannot be suppressed.

### 2.5 Sample Matrix Inversion (SMI)

In this method, a $K$-length block of data is used. Thus, it is usually called a block-adaptive approach where the weights are adapted block-by-block basis.

For $k$th block of length $K$, the weights can be calculated as [19]

$$
\tilde{w}(k) = [\bar{X}_K(k)\bar{X}_K^H(k)]^{-1}d(k)\bar{X}_K(k)
$$

(10)

This method has some advantages in the application where the characteristics of the desired signal may change rapidly. The SMI algorithm has the ability to track such changes due to its high rate of convergence. Unlike the LMS algorithm, the SMI estimates the covariance matrix using $K$-time samples. The nulling capability of this algorithm is shown in Figure 6 for block length equal to $K=100$ and $N=12$ controllable elements. It can be seen that its performance for interference suppression is satisfactory.

Although all or most of the above-mentioned algorithms are able to reshape the array pattern to reduce the effect of interfering signals, but they still suffer from low convergence speed due to many unavoidable iterations and high complexity in the feeding network due to the fact that each controllable element in the array needs at least one set of variable attenuator and variable phase shifter. These RF components need to be very accurate to achieve the required nulls. Any approximation in the weight’s value will be at the cost of moving the nulls from their desired directions. Thus, none of the above-mentioned methods are desirable in practice. The need for a simple and effective solution to this important problem is potentially required. One solution is addressed in the following section.

### 3. The Proposed Adaptive Array
Figure 7 shows the block diagram of the proposed adaptive array. It implies an adaptive controller based LMS algorithm, and only a small number of the controllable elements, say M elements, with another number of uncontrollable elements, N-M elements. For the purpose of reducing the complexity of the feeding network and maximally exploiting the number of degrees of freedom for null steering, the number of the uncontrollable elements is selected to be much larger than the number of controllable elements, i.e., \((N - M) > M\). This selection is mainly relay on the interference environment specifically on the number of the interfering signals where it should be noted that for efficient suppression of the interfering signals the number of the controllable elements should be at least equal to the number of interfering signals, i.e., \(M \geq I\).

In some applications that use large arrays, the number of the interfering signals may be much smaller than the number of the array elements. In this case, only a small number of the degrees of freedom instead of all of them are sufficient to achieve the required nulling. Thus, selecting a small and sufficient number of the elements to be controllable is one of the effective solutions to significantly reduce the complexity of the feeding network and accelerate the convergence speed of the adaptive algorithm while maintaining excellent suppression for interfering signals.

Although the concept of adaptive algorithms is not new, the idea of controlling only a small number of the array elements via LMS algorithm is new and it has not been previously investigated to the best of author’s knowledge. Many other advantages of the proposed adaptive array are explained on the following section.

![Block diagram of the proposed adaptive array.](image-url)
4. Simulation Results
Extensive numerical examples are provided in this section to illustrate the performance, in terms of pattern nulling, accurate null steering, null depths, convergence speed of the adaptive algorithm, and the complexity of the feeding network of the proposed array. The considered antenna array consists of $M$ controllable elements and $N-M$ uncontrollable elements as shown in Figure 7. The uncontrollable elements are excited with uniform excitation. All of the array elements are assumed to lie along the $x$-axis with an element distance of $d = \lambda/2$.

In the first example, we used the proposed array that presented in section III to steer the required nulls with only $M=4$ controllable elements. Figure 8 shows the radiation pattern of the proposed array. Compare Figure 8 with that of Figure 2 for fully controllable array elements, it can be seen that the proposed array pattern with only 4 controllable elements is comparable to that of the popular LMS based fully controllable array elements for placing the required nulls. More important, the main beam shape of the proposed array is very close to that of the desired uniform array pattern (the half power beam widths (HPBW) of the proposed array and the uniform array patterns are $11.66^\circ$ and $11.6^\circ$ respectively).

In the second example, the updating process of the controllable elements in both arrays is shown in Figure 9. It can be seen that the four controllable weights are much easier to update and control over the method that consists of twelve controllable elements.

In the last example, the convergence speed of the adaptive algorithm in both arrays are compared and shown in Figure 10. It can be seen that the MSE of the proposed array is much smaller than that of the popular LMS array. Moreover, the proposed array requires only 15 iterations to converge while the popular LMS array needs at least 60 iterations to converge. These results fully confirm the effectiveness of the proposed array.

![Figure 8](image8.png)

**Figure 8.** Proposed array pattern for only 4 controllable elements and 8 uncontrollable elements (solid) and Popular LMS

![Figure 9](image9.png)

**Figure 9.** Updating of the controllable weights in the popular LMS array (left), and the proposed array (right).
5. Conclusions
Adaptive arrays are most powerful methods for interference suppression in the rapidly changing environments. However, there are some difficulties in implementing them in practice. These difficulties include complex feeding network and slow convergence speed of the adaptive algorithm especially when arrays imply large number of elements. In this paper, these difficulties are overcome by considering only a small subset of the array elements to be controllable. Simulation results have shown that the performance of the proposed array is comparable to that of fully controllable array with less complexity in the feeding network and faster convergence speed. Moreover, the subset of the controllable elements is capable to steer the required nulls.

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![Figure 10. Convergence speed of the tested arrays.](image-url)
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