A Hybrid Adaptive Beamforming Algorithm for SINR Enhancement in Massive MIMO Systems

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Abstract. *With the extreme density of devices and fast change of their directions in massive MIMO networks, a fast adaptive beamforming algorithm is required to provide high directivity and an enhanced signal-to-interference and noise ratio (SINR). Blind adaptive beamforming is suitable but less efficient, while non-blind adaptive beamforming is more efficient but requires significant training time. This study proposes a hybrid adaptive beamforming algorithm that addresses these issues. The algorithm integrates an improved direction-finding method to estimate the directions of arrival (DoAs) of incident signals at the antenna array, even in coherent signals cases, and a cascading combination of a blind and non-blind algorithms. The proposed algorithm generates an accurate main beam toward the desired direction and deep nulls in the direction of interfering signals, resulting in enhanced SINR. Compared to other algorithms, our approach achieves better performance without requiring additional antenna elements.*

Keywords

Massive MIMO, adaptive beamforming, interference cancellation, direction-of-arrival estimation, SINR enhancement

1. Introduction

A Massive Multiple-input Multiple-output (mMIMO) system operates a large number of smart antenna elements at the transmitter side and the receiver side, where combining it with the beamforming technique presents a key features to enhance performance in next-generation networks in terms of coverage and interference mitigation [1], [2].

The beamforming technique is a signal processing procedure that forms a directional signal beam between the transmitter side and the receiver side by exploiting an antenna element array. It focuses the signal beam in a specific direction, enhancing the signal strength at the receiver and reducing interference levels, resulting in increased spectral efficiency and system capacity [2].

For mMIMO systems, the adaptive beamforming (ABF) technique is more appropriate than the conventional beamforming because of its capability to cancel interference. Then the optimal SINR can be achieved. Adaptive beamforming is a technique that steers the main beam toward the desired direction while adaptively eliminating the interfering signals by generating nulls towards the undesired directions using an array of antenna elements, by adjusting the elements' control complex weights until a specified goal function is met [3], [4]. Consequently, an adaptive beamforming algorithm automatically optimizes the array pattern.

There are two different types of adaptive beamforming algorithms: the non-blind ABF algorithm and the blind ABF algorithm [5–7]. The non-blind adaptive beamforming algorithm requires statistical knowledge about the signal to converge the complex weights to optimal values. This is achieved by using a pilot training sequence that is transmitted over the channel to the receiver to assist in updating the complex weights of the array. The non-blind ABF algorithm is based on the minimization of mean square error (MSE) between the training signal and the received signal. It can generate deep nulls toward interfering signals compared to the blind adaptive beamforming [6].

The blind adaptive beamforming algorithm takes advantage of the features of the system to continually update complex weights to pursue channel changes. There are two categories of blind adaptive beamforming: the first category is based on the DoA estimation result. This type of algorithm produces complex weights based on DoA estimation using certain formulae, while the second category is based on certain characteristics of the desired signal [7].

As a result of using prior data compared to the blind beamforming algorithm, the non-blind algorithm has a quicker convergence rate and simpler computing complexity. However, the sending of training sequences decreases transmission efficiency, particularly at high speeds [8].

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The next-generation network requires mMIMO technique and mm-wave band to achieve a very high data rate [9]. Therefore, to make millimeter-wave adaptive beamforming possible, blind ABF is appropriate for application to the mMIMO system, especially the MVDR algorithm which is considered more convenient compared to other blind ABF algorithms [10].

In this paper, we propose a new hybrid ABF algorithm solution for mMIMO that takes advantage of two categories of ABF. Our proposed ABF algorithm is based on a combination of the DoA estimation method and an adaptive spatial signal processing method. First, the estimation of incident signal sources' directions is considered a challenging task in the field of signal processing. Among various algorithms, the Multiple Signal Classification (MUSIC) algorithm is the most popular. It is based on the eigenvalue decomposition of the array covariance matrix, providing a low computational load and high-resolution capability [11]. However, the MUSIC algorithm has limitations in estimating the spatial spectrum of signals precisely when impinging signals are coherent [12]. To overcome this problem, we propose an improved MUSIC (IMUSIC) method.

Secondly, the proposed adaptive spatial signal processing method steers the signal main beam towards the desired direction and generates deep nulls towards the directions of interfering signals, based on the estimated DoAs using the IMUSIC method. This is achieved by cascading the Minimum Variance Distortionless Response (MVDR) method, a blind adaptive beamforming method, with the Recursive Least Squares (RLS) method, a non-blind adaptive beamforming method. Initially, the RLS method uses the complex weights obtained by the MVDR method to rapidly interact with the initial signal sources' positions. Subsequently, these complex weights are adjusted to cancel the interfering signals and achieve a high SINR.

In this context, we perform several simulations to compare the DoA estimation methods to determine the best method for detecting signal sources with stability and high resolution in different scenarios. Additionally, simulations are conducted to compare the ABF algorithms in terms of null placement towards interfering signals to identify the best ABF algorithm that can mitigate interferences and achieve the highest SINR.

This paper is structured as follows: Section 2 provides a review of related works, Section 3 presents the proposed hybrid adaptive beamforming algorithm, Section 4 presents the simulation results, and finally, the conclusion is presented in Sec. 5.

2. Related Works

This section provides a detailed mathematical model for adaptive beamforming. Accordingly, we consider a uniform linear antenna array (ULA) consisting of M antenna elements with a uniform distance d_x between two adjacent elements. The antenna array receives signals from K-independent sources, including desired and interference signals, impinging on the array from different angles θ, where θ_k is the angle of arrival of the k-th incident signal.

We assume that T snapshots (time samples) are available, and the signal received by the adaptive antenna array at snapshot t is expressed as:

$$\begin{aligned} x(t) &= As(t) + n(t) \\ &= a(\theta_d)s_d(t) + \sum_{i=1, i\neq d}^{K} a(\theta_i)s_i(t) + n(t) \end{aligned} \tag{1}$$

where $d, i \in [1, \ldots, K]$, and $t \in [1, \ldots, T]$.

Furthermore, $s(t) \in \mathbb{C}^{K\times 1}$ is the vector of complex amplitudes of the signal sources at snapshot t, $s_d(t)$ is the complex amplitude of the desired signal source, $s_i(t)$ is the complex amplitude of the i-th interfering signal source, $n(t) \in \mathbb{C}^{M\times 1}$ is the additive white Gaussian noise, $A = [a(\theta_1), \ldots, a(\theta_K)] \in \mathbb{C}^{M\times K}$ is the matrix of the steering vectors whose columns are the steering vectors for all the possible angles of arrival, $\theta = [\theta_1, \theta_2, \ldots, \theta_K]$ is the vector of angles of arrival, in which $a(\theta_k) \in \mathbb{C}^{M\times 1}$ is the steering vector for the k-th signal source with angle of arrival θ_k can be written as follows:

$$a(\theta_k) = \begin{bmatrix} 1 \\ \mathrm{e}^{\mathrm{j}\left(\frac{2\pi}{\lambda} d_x \cos\theta_k\right)} \\ \vdots \\ \mathrm{e}^{\mathrm{j}\left(\frac{2\pi}{\lambda} d_x \cos\theta_k (m-1)\right)} \end{bmatrix} \tag{2}$$

where $m \in [1, \ldots, M]$, $k \in [1, \ldots, K]$.

As well λ is the wavelength of received signal, and d_x is the elements spacing. Therefore, the array pattern can be written as follows:

$$AF(\theta) = w^{\mathrm{H}} a(\theta) \tag{3}$$

where $w \in \mathbb{C}^{M\times 1}$ is the complex weights vector for the antenna elements and $(\cdot)^{\mathrm{H}}$ denote the Hermitian.

The mathematical model for adaptive beamforming consists of two parts. The first part involves estimating the directions of incident signal sources by estimating the DoA of each signal. Once the DoAs have been estimated, the second part of the model generates an adaptive spatial signal.

Adaptive beamforming is a powerful signal processing technique that has been widely applied in various fields, such as sonar, radar, and recently in wireless communication systems. Its ability to detect the DoAs of incident signals and steer the main beam toward the desired signal direction, while providing nulls in the interfering signals' directions has made it an indispensable tool for achieving better performance and wider coverage [2, 8, 13, 14]. By adjusting the complex weights of antenna elements, an adaptive beamformer can automatically optimize the array pattern to maximize the output power in the direction of the desired signal while minimizing the output power in interfering signals' directions. This technique has proven to be effective in combating issues such as multipath fading, noise, and interference [5, 15, 16]. The result is an enhanced SINR, channel capacity, and maximum gain.

In the context of mMIMO systems, adaptive beamforming can provide a means to separate different co-channel users by exploiting the spatial dimension [5], [15]. As a result, the system can counteract interference towards the intended signal, leading to improved signal quality and increased capacity. The effectiveness of adaptive beamforming is reflected in the general equation of array output at time t, which is given as [16]:

$$y(t) = w^{\mathrm{H}}(t)x(t). \tag{4}$$

As well, the complex weights can be calculated based on the array in an iterative manner. So, the adaptive beamforming algorithms are classified into two-categories: non-blind adaptive algorithms and blind adaptive algorithms.

Non-blind adaptive beamforming algorithms as shown in Fig. 1 update the complex weights of the array continuously thanks to a training signal $d(t)$ similar to the original signal, this training signal is sent to the receiver during a training time interval. Afterward, the adaptive array output is compared to the training signal at the end of each iteration to generate an error signal that is used to adjust the complex weights of the array. The error signal can be written as follows:

$$e(t) = d(t) - y(t). \tag{5}$$

To achieve optimal performance, non-blind adaptive beamforming algorithms adjust the complex weights of antenna elements to minimize the difference between the reference signal and the array output signal. This allows the algorithms to accurately track the user with a main beam directed towards the desired signal and generate nulls in the direction of interfering signals. Several non-blind adaptive beamforming algorithms have been developed, including the least-mean-square (LMS), RLS, and sample-matrix-inversion (SMI) algorithms, which are among the most popular [17], [18].

In contrast to non-blind adaptive beamforming algorithms, the blind adaptive beamforming algorithm shown in Fig. 2 does not require the direct transmission of a training signal sequence. Instead, it continuously adjusts the complex weights of the antenna element array based on the system's characteristics to track changes in the channel. Blind ABF methods fall into two categories. The first category exploits certain formulas to produce complex weights based on the estimation of the DoAs of the incident signals at the antenna array, such as the estimation of signal parameters via rotational invariant techniques (ESPRIT) and MUSIC algorithms. The second category exploits certain formulas based on the characteristics of the desired signal, such as the Constant Modulus (CM) algorithm [7].

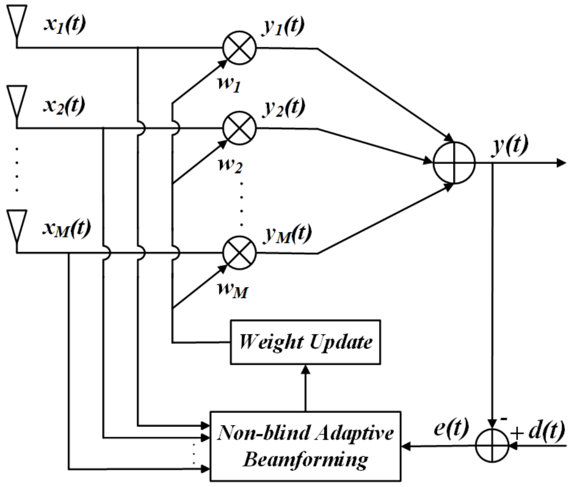

Fig. 1. Structure of the Non-Blind adaptive beamforming.

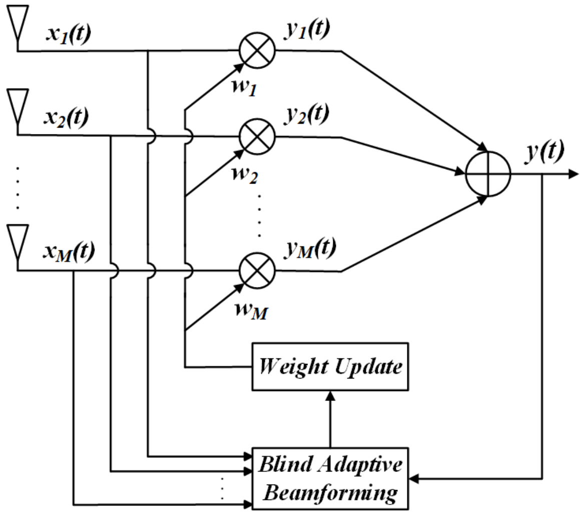

Fig. 2. Structure of the Blind adaptive beamforming.

On the other hand, the most well-known blind adaptive algorithms include the Constant Modulus Algorithm (CMA), the Decision-Directed Algorithm (DD), and the Least Squares Constant Modulus Algorithm (LS-CMA) [19].

It is important to carefully consider the choice between non-blind and blind adaptive methods for signal processing, as the selection depends on various factors. Non-blind methods typically use more prior information, resulting in faster convergence and simpler computational complexity. However, sending a training signal sequence can reduce transmission efficiency, especially in dense networks or fast mobility environments where devices change direction rapidly. In such cases, transmitting the training signal within a limited time window can be challenging.

In contrast, blind adaptive methods do not require sending a training signal sequence and can exploit the system's characteristics directly. This can be advantageous when sending a training signal is difficult or infeasible. However, in complex or rapidly changing environments, blind methods may not achieve the same level of performance as non-blind methods that use more prior information.

Therefore, the choice between non-blind and blind methods should be based on careful consideration of various factors, including the available resources, the complexity of the environment, and the desired level of performance.

In recent years, research on beamforming techniques has evolved due to the rapid advancement of wireless communication systems. In [20–22] the authors studied the employments of beamforming in millimeter-wave communication systems. Furthermore, the beamforming technique for highspeed device environments has become a hot topic in the wireless communication research area where authors in [23] analyzed the features of a line of sight (LoS) and fast time varying channels in a fast mobility scenario. Moreover, estimating the DoAs of incident signals at the antenna array is a fundamental issue in array signal processing to complete the adaptive beamforming operation. Therefore, numerous DoA estimation algorithms have been proposed in [24], [25] for their solutions.

Based on next-generation wireless networks requirement that includes accuracy or no latency to get the highest SINR for the desired device, blind adaptive methods are more convenient than non-blind adaptive methods for massive MIMO systems.

Recently, two well-known blind methods have been developed: the Linear Constraint Minimum Variance (LCMV) beamforming method [26] and the MVDR beamforming method [27]. As a consequence, the mentioned properties of LCMV and MVDR indicate that MVDR is more convenient for massive MIMO systems than LCMV.

In this work, we investigate the performance of both the blind and non-blind methods for adaptive beamforming. Accordingly, we propose a hybrid adaptive beamforming algorithm that combines the strengths of the blind method, represented by the MVDR algorithm, with those of the non-blind method, represented by the RLS algorithm. Our proposed algorithm relies on an Improved-MUSIC method to accurately estimate the DoA of impinging signals at the array.

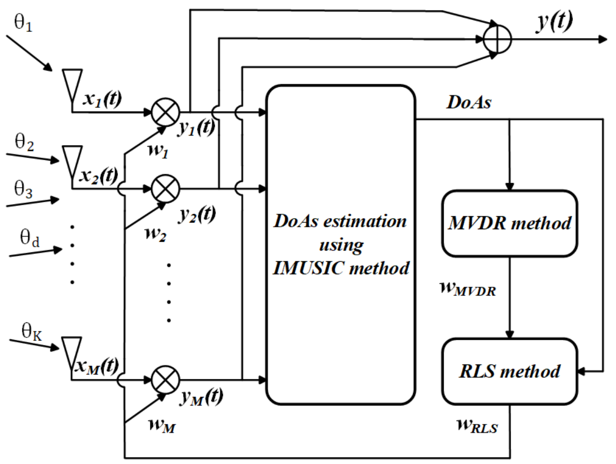

Fig. 3. Block diagram of the proposed hybrid adaptive beamforming algorithm.

3. Proposed Hybrid Adaptive Beamforming Algorithm

The proposed hybrid adaptive beamforming algorithm, as illustrated in Fig. 3, is based on two fundamental processes: a DoA estimation method and an adaptive spatial signal processing method. The first process employs an improved MUSIC method to estimate the DoAs of incident signals at the array. The proposed estimation method is efficient in distinguishing between coherent incident signals at the array, resulting in the accurate determination of DoAs.

The second process is a cascade combination of two adaptive beamforming algorithms. In the first phase, the MVDR algorithm, a blind ABF algorithm, is utilized. The second phase employs the RLS algorithm, a non-blind ABF algorithm. The RLS method leverages the initial complex weights of the MVDR method to provide a rapid start in detecting the initial device position and producing nulls in the interference directions while tracking the desired direction.

Furthermore, these two adaptive beamforming techniques receive feedback from the proposed IMUSIC method to continuously locate the DoAs of different signal sources.

3.1 Proposed DoAs Estimation Method

The MUSIC algorithm is a high-resolution method for estimating the DoAs of signals. It is based on the eigenvalue decomposition of the array covariance matrix R_x, which allows us to determine the K eigenvectors corresponding to the signals and the $(M-K)$ eigenvectors corresponding to the noise [28]. By analyzing the received signal at the array, we can obtain its covariance matrix R_x as follows:

$$\begin{aligned} R_x &= E\left[x(t)x^{\mathrm{H}}(t)\right] \\ &= AE\left[s(t)s^{H}(t)\right]A^{\mathrm{H}} + \sigma_n^2 I_M \\ &= AR_sA^{\mathrm{H}} + R_M \end{aligned} \tag{6}$$

where R_s is the source signal covariance matrix such as $\mathrm{rank}(AR_sA^{\mathrm{H}}) = K$, R_M is the noise covariance matrix, σ_n^2 is the noise power at each antenna element and I_M is the $M \times M$ identity matrix. Practically, the covariance matrix R_x usually is unavailable. However, a maximum likelihood estimation of this matrix according to the finite number of snapshots T is attainable as:

$$R_x = \frac{1}{T}\sum\nolimits_{t=1}^{T} x(t)x^{\mathrm{H}}(t). \tag{7}$$

The covariance matrix R_x contains M eigenvalues $(\pi_1, \pi_2, \ldots, \pi_M)$ corresponding to the M eigenvectors $(q_1, q_2, \ldots, q_M)$ which are orthogonal to each other:

$$q_i^{\mathrm{H}} q_j = 0 \tag{8}$$

where $i \neq j$.

Then, for the data signal, the number of associated eigenvalues is K while for the noise the number of associated eigenvalues is $M - K$. As well, the eigendecomposition of the covariance matrix R_x exploiting to find the DoAs can be defined in a consistent manner:

$$R_x = Q_s \Pi_s Q_s^{\mathrm{H}} + Q_n \Pi_n Q_n^{\mathrm{H}} \tag{9}$$

where

$$\begin{aligned} Q_s &= [q_1, q_2, \ldots, q_K], \\ Q_n &= [q_{K+1}, q_{K+2}, \ldots, q_M], \\ \Pi_s &= \operatorname{diag}\{\pi_1, \pi_2, \ldots, \pi_K\}, \\ \Pi_n &= \operatorname{diag}\{\pi_{K+1}, \pi_{K+2}, \ldots, \pi_M\}. \end{aligned} \tag{10}$$

In fact, Π_s represents the eigenvalues vector and Q_s represents the eigenvectors matrix corresponding to the source signal subspace, while Π_n and Q_n represent the eigenvalues vector and eigenvectors matrix of the noise subspace, respectively. This decomposition method is crucial for determining the DoAs of incident signals at the antenna array accurately.

However, the conventional MUSIC method is only suitable for estimating the DoAs of incoherent impinging signals. This method loses performance when dealing with correlated or low Signal-to-Noise Ratio (SNR) signals, leading to inaccurate results in such scenarios.

When coherent signals are received, combining them into a single signal reduces the number of independent signals and consequently, reduces the rank of the covariance matrix R_x. As a result, the spatial-spectral curve has fewer peaks, making it difficult to accurately estimate the DoAs of the incoming signals. To address this problem and effectively estimate the DoAs of different correlated signals, it is necessary to eliminate the correlation between the incoming signals. This can be achieved by introducing a new matrix $z(t)$, which decorrelates the incoming signals. The new matrix $z(t)$ is defined as follows:

$$z(t) = J_M x^*(t) \tag{11}$$

where $x^*(t)$ is the complex conjugate of $x(t)$ and J_M is the reversal matrix with $M \times M$ dimensions can be represented as follows:

$$J_M = \begin{bmatrix} 0 & 0 & \cdots & 0 & 1 \\ 0 & 0 & \cdots & 1 & 0 \\ \vdots & \vdots & \iddots & \vdots & \vdots \\ 0 & 1 & \cdots & 0 & 0 \\ 1 & 0 & \cdots & 0 & 0 \end{bmatrix}. \tag{12}$$

Then, the covariance matrix of $z(t)$ can be expressed as:

$$\begin{aligned} R_z &= E\left[z(t) z^{\mathrm{H}}(t)\right] \\ &= J_M R_x^* J_M. \end{aligned} \tag{13}$$

Therefore, the covariance matrix can be reconstructed as follows:

$$\begin{aligned} R &= (R_x + R_z)/2 \\ &= (R_x + J_M R_x^* J_M)/2 \\ &= \mathrm{Q}_{ns} \Pi_{ns} Q_{ns}^{\mathrm{H}} + \mathrm{Q}_{nn} \Pi_{nn} Q_{nn}^{\mathrm{H}}. \end{aligned} \tag{14}$$

Based on matrix theory, the noise subspace of the matrices R_x, R_z, and R is the same. To estimate the DoAs values of incident signals, the typical decomposition of the matrix R should be conducted, according to the estimated number of signal sources. This decomposition leads to obtaining the new eigenvalues Π_{ns} and the new eigenvectors Q_{ns} of the signal subspace, as well as the new eigenvalues Π_{nn} and the new eigenvectors Q_{nn} of the noise subspace. The new noise subspace can then be used to construct a spatial spectrum using the following function:

$$F_{\mathrm{IMUSIC}}(\theta) = \frac{1}{a^{\mathrm{H}}(\theta) Q_{nn} Q_{nn}^{\mathrm{H}} a(\theta)}. \tag{15}$$

Over the angular field-of-view, the largest K peaks produced by spectrum function F_{IMUSIC} are used to estimate the different DoAs of the impinging signal sources.

3.2 Proposed Adaptive Signal Processing Method

The proposed adaptive signal processing method combines the advantages of both the MVDR and RLS methods. Initially, the MVDR method is used to obtain the initial complex weights, which are utilized to rapidly interact with the signal sources locations. The MVDR algorithm is capable of directing the array output response towards the desired signal's specific direction and suppressing interfering signals by creating nulls towards their directions. Once the initial interaction with signal sources is complete, the RLS method is employed to create severe and deep nulls towards interfering signal sources. This combined approach results in a more efficient and accurate signal processing method.

The complexity of a hybrid adaptive beamforming algorithm that combines MVDR for the desired signal and RLS for interference suppression, can be higher than MVDR or RLS algorithms alone due to the added complexity of combining the two methods. However, the performance gains in terms of better interference suppression and desired signal enhancement may be worth the additional complexity.

The MVDR algorithm relies on the steering vectors, which in turn depend on the DoA of the impinging signal at the elements of the antenna array [27]. To minimize the output power subject to a unity gain constraint in the direction of the desired signal, knowledge of the direction of the desired signal is required. The array output power can be calculated as follows:

$$\begin{aligned} P &= \left\{\mathrm{E}|y|^2\right\} = \mathrm{E}\left\{w^{\mathrm{H}} x x^{\mathrm{H}} w\right\} \\ &= w^{\mathrm{H}} \mathrm{E}\left\{x x^{\mathrm{H}}\right\} w = w^{\mathrm{H}} R w \end{aligned} \tag{16}$$

where $\mathrm{E}[.]$ is the expectation operator.

Indeed, the array output power using MVDR spatial spectrum is able to estimate the DoAs by detecting the peaks in this angular spectrum.

In this work, we use the reconstructed covariance matrix R that can be explained by:

$$\begin{aligned} R &= \sigma_d^2 a(\theta_d) a^{\mathrm{H}}(\theta_d) + \sum_{i=1, i\neq d}^{K} \sigma_i^2 a(\theta_i) a^{\mathrm{H}}(\theta_i) + \sigma_n^2 I_M \\ &= R_d + R_{i+n} \end{aligned} \tag{17}$$

where $\sigma_d^2, \sigma_i^2, \sigma_n^2, I_M$ denotes the desired signal power, the interfering signals power, noise power, and $M \times M$ identity matrix respectively. Additionally, R_d corresponds to the covariance matrix of the desired signal, while R_{i+n} corresponds to the covariance matrix of the interfering signals and noise.

MVDR algorithm optimizes complex weights to maximize SINR for enhancing desired signals and reducing noise and interference. The output SINR of the MVDR beamformer can be derived from the SINR equation as follows [27]:

$$SINR = \frac{w^{\mathrm{H}} R_d w}{w^{\mathrm{H}} R_{i+n} w}. \tag{18}$$

To obtain the optimal complex weight vector w_{MVDR} for the MVDR beamformer, we need to solve the following constrained problem [27]:

$$\begin{aligned} \min_w \quad & w^{\mathrm{H}} R_{i+n} w, \\ \text{s.t.} \quad & w^{\mathrm{H}} a(\theta_d) = 1. \end{aligned} \tag{19}$$

By reducing the output power of interference and noise guaranteeing that the power of the desired signal is equal to 1, this technique minimizes the contribution of the interfering signals. Subsequently, the MVDR complex weights vector can then be obtained using the equation below [27]:

$$w_{\mathrm{MVDR}} = \frac{R_{i+n}^{-1} a(\theta)}{a^{\mathrm{H}}(\theta) R_{i+n}^{-1} a(\theta)}. \tag{20}$$

The RLS method is known for its fast convergence rate, making it a preferred choice over other methods such as the LMS method, especially in scenarios where the covariance matrix R has a large eigenvalue spread. The main difference between the RLS method and the LMS method lies in their approach towards adapting the filter coefficients. Specifically, in the RLS method, the inverse of the covariance matrix replaces the step size parameter used in the LMS method, while the gain matrix replaces the gradient step size [29].

The RLS algorithm requires an estimate of the covariance matrix R and the covariance vector r to update the tap complex weight vector at each time sample t, based on the least squares estimate of the tap complex weight vector at the previous time sample $t-1$. This allows the RLS algorithm to track changes in the signal sources over time. The correlation matrix and vector are estimated using a weighted estimate technique that emphasizes more recent data samples while de-emphasizing earlier ones.

The covariance matrix and vector are estimated using a forgetting factor α, which is used to assign weights to the past data samples. This can be expressed as follows:

$$\begin{aligned} R(t) &= \sum_{p=1}^{t} \alpha^{t-p} x(p) x^{\mathrm{H}}(p), \\ r(t) &= \sum_{p=1}^{t} \alpha^{t-p} d^*(p) x(p) \end{aligned} \tag{21}$$

where α is a positive constant $0 \leq \alpha \leq 1$ called 'the forgetting factor', which is a parameter that governs how much weight is given to past measurements in the current estimate. A forgetting factor of 1 implies that all past measurements are equally weighted in the current estimate, whereas a forgetting factor of 0 indicates that only the most recent measurement is considered. The choice of the forgetting factor depends on the specific application and the desired trade-off between tracking speed and stability.

The summation in the covariance matrix R and the covariance vector r can be decomposed into two parts, the first for p values up to $p-1$ and the second for $p = t$, as follows:

$$\begin{aligned} R(t) &= \alpha \sum_{p=1}^{t-1} \alpha^{t-1-p} x(t) x^{\mathrm{H}}(t) + x(t) x^{\mathrm{H}}(t) \\ &= \alpha R(t-1) + x(t) x^{\mathrm{H}}(t), \\ r(t) &= \alpha \sum_{p=1}^{t-1} \alpha^{t-1-p} d^*(p) x(p) + d^*(t) x(t) \\ &= \alpha r(t-1) + d^*(t) x(t). \end{aligned} \tag{22}$$

Therefore, we can establish a recursive formula to update the tap complex weight vector in the RLS algorithm by computing the inverse of the covariance matrix. The gain vector $g(t)$ is obtained using the inverse of the covariance matrix, denoted as $R^{-1}(t)$, which is utilized to update the tap complex weight vector.

The Sherman-Morrison-Woodbury (SMW) theorem is employed to calculate the inverse of the covariance matrix. This theorem specifies that if we have an invertible matrix B and make a small $rank - 1$ adjustment to B in the form of $B + uu^{\mathrm{H}}$, we can determine the updated inverse of the matrix using the inverse of the initial matrix and the vector u as given below [30]:

$$\left(B - uu^{\mathrm{H}}\right)^{-1} = B^{-1} - \frac{B^{-1} u u^{\mathrm{H}} B^{-1}}{1 + u^{\mathrm{H}} B^{-1} u}. \tag{23}$$

Thus, the inverse covariance matrix can be expressed as follows:

$$\begin{aligned} R^{-1}(t) &= \alpha^{-1} R^{-1}(t-1) - \frac{\alpha^{-2} R^{-1}(t-1) x(t) x^{\mathrm{H}}(t) R^{-1}(t-1)}{1 + \alpha^{-1} x^{\mathrm{H}}(t) R^{-1}(t-1) x(t)} \\ &= \alpha^{-1} R^{-1}(t-1) - \alpha^{-1} g(t) x^{\mathrm{H}}(t) R^{-1}(t-1). \end{aligned} \tag{24}$$

Then, the gain factor $g(t)$ is given by:

$$\begin{aligned} g(t) &= \frac{\alpha^{-1} R^{-1}(t-1) x(t)}{1 + \alpha^{-1} x^{\mathrm{H}}(t) R^{-1}(t-1) x(t)} \\ &= \alpha^{-1} R^{-1}(t-1) - \alpha^{-1} g(t) x^{\mathrm{H}}(t) R^{-1}(t-1) x(t) \\ &= R^{-1}(t) x(t). \end{aligned} \tag{25}$$

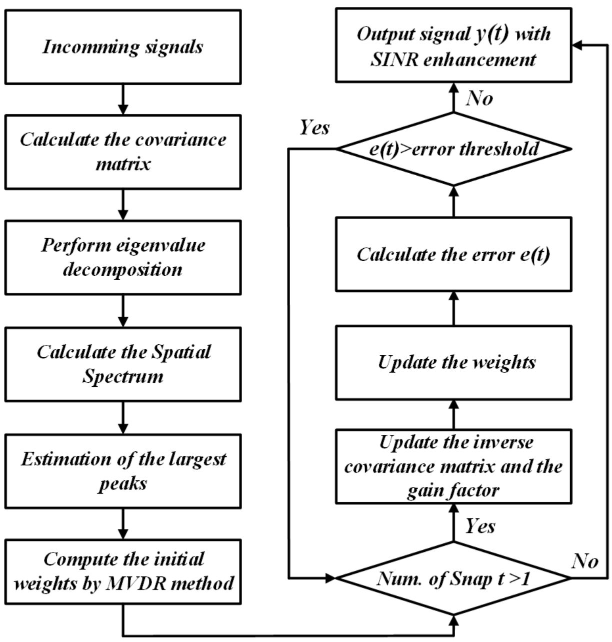

Fig. 4. Flowchart of the proposed hybrid ABF algorithm.

As result, the recursive equation for updating the tap-weights vector in terms of the time sample t is:

$$\begin{aligned} w_{\text{RLS}}(t) &= R^{-1}(t)r(t) \\ &= w_{\text{RLS}}(t-1) - g(t)x^{\text{H}}(t)w_{\text{RLS}}(t-1) + g(t)d^*(t) \\ &= w_{\text{RLS}}(t-1) + g(t)\left[d^*(t) - x^{\text{H}}(t)w_{\text{RLS}}(t-1)\right]. \end{aligned} \tag{26}$$

Consequently, the priori estimation error is:

$$\begin{aligned} e(t) &= d(t) - x^{\text{T}}(t)w^*_{\text{RLS}}(t-1) \\ &= d(t) - w^{\text{H}}_{\text{RLS}}(t-1)x(t). \end{aligned} \tag{27}$$

The inner product $w^{\text{H}}_{\text{RLS}}(t-1)x(t)$ constitutes an estimate of the desired signal $d(t)$, based on the previous least-squares estimate of the tap-weights vector at time sample $t-1$. Additionally, the proposed algorithm benefits from the constant initial complex weights of the MVDR technique to provide a fast start. Then, it computes the a priori estimation error for each snapshot until the error reaches a threshold value, indicating that convergence has been achieved and the optimal complex weights have been obtained.

The proposed algorithm can be summarized in the flowchart as shown in Fig. 4.

4. Simulation Results

Simulation results are presented in this section. Firstly, the proposed DoA estimation method, referred to as "IMUSIC", is used to determine the different directions of incoming signals at the antenna array with high resolution. The proposed method is compared with other methods such as MUSIC and MVDR to test its capability to estimate DoAs, particularly in the case of coherent signals.

Secondly, simulation results are carried out to stand on the best blind adaptive beamforming algorithm and the best non-blind adaptive beamforming algorithm. Moreover, the simulation results are carried out to appear the proposed hybrid adaptive beamforming efficiency, which exploits a cascade between the MVDR and the RLS algorithms to adjust the complex weights based on estimated DoAs information, and produce an optimal main beam pattern toward the desired signal direction and severe nulls toward the directions of the interfering signals to enhance the SINR. Thereafter, the proposed algorithm is compared to other algorithms such as MVDR and RLS. All simulations were performed using ULA composed of $M = 32$ elements with uniform element spacing $d_x = \frac{\lambda}{2}$.

4.1 DoAs Estimation Results

To stand on the better DoA estimation method, we generate the spectrum of the MVDR, MUSIC, and the proposed IMUSIC methods. Consider that there are $K = 2$ incident signals on the above-mentioned antenna elements array from the directions (30° and 60°). Two test scenarios were carried out to estimate the DoAs using the MVDR, MUSIC, and proposed IMUSIC methods.

In the first scenario, we assumed that both incoming signals at the array were incoherent, with 5 dB and $T = 100$ snapshots, where Fig. 5 shows the spectrums of MVDR, conventional MUSIC, and proposed IMUSIC techniques.

It is clear that the three methods provide sharp peaks at the intended signals directions on the antenna elements array, with high amplitudes equal to 0 dB, which can be predicted by the receiver. While the highest noise levels at the unintended directions are < -30 dB, where IMUSIC method generates the lowest noise levels. However, the proposed IMUSIC provides better resolution, which provides the narrowest peaks and the lowest noise levels as compared to the conventional MUSIC method which in turn is better than the MVDR method.

In the second scenario, both two incoming signals at the array are coherent. Then, the $SNR = 5$ dB, and the number of snapshots is set as $T = 100$. The resultant spatial spectrums of the three techniques are depicted in Fig. 6.

It is obvious that the IMUSIC method provides an accurate estimation of the incoming signals directions. The IMUSIC method generates narrow peaks at the intended directions with amplitudes equal to 0 dB and the noise levels is < -40 dB at the unintended directions. While MVDR and MUSIC methods generate wide peaks at the intended directions and a noise levels > -4 dB at the unintended directions. So, under the same conditions, the proposed IMUSIC method provides the narrowest peaks and the lowest noise levels by a large margin than the conventional MUSIC and the MVDR methods. So, contrary to the others methods, IMUSIC easily removes the correlation between the signals.

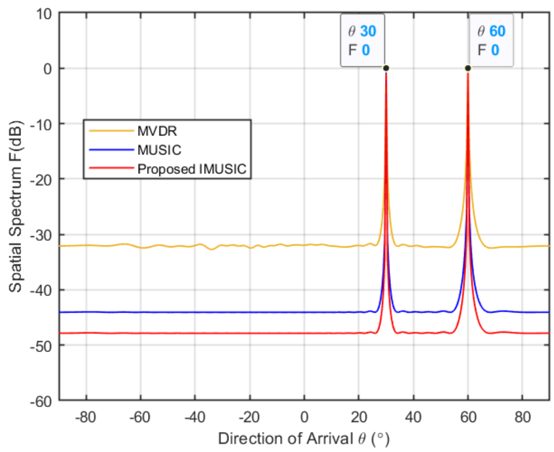

Fig. 5. Spatial spectrum of MVDR, MUSIC and the proposed IMUSIC methods in the case of incoherent signals.

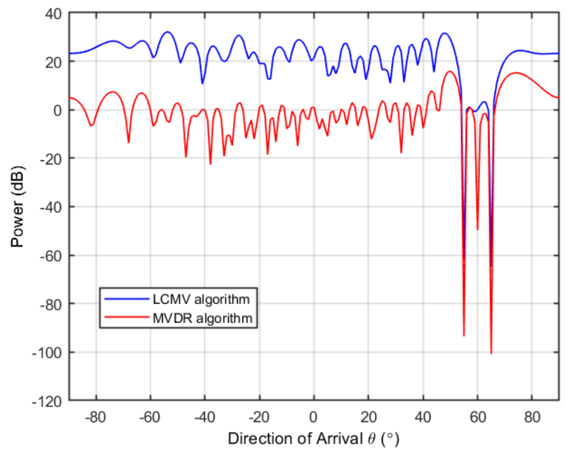

Fig. 7. Response pattern of the LCMV and MVDR algorithms.

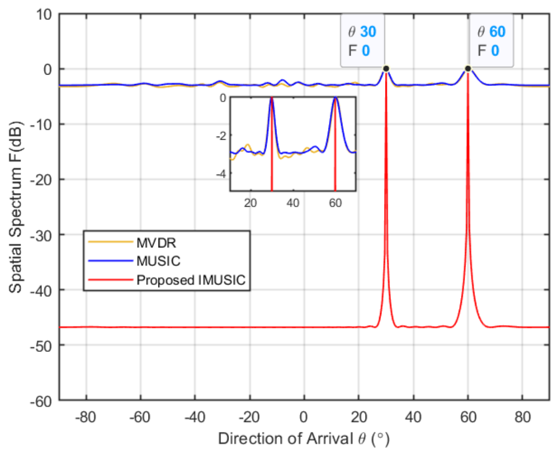

Fig. 6. Spatial spectrum of MVDR, MUSIC and the proposed IMUSIC methods in the case of coherent signals.

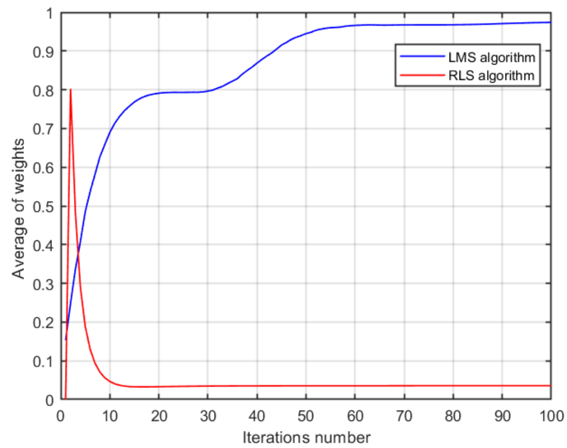

Fig. 8. Convergence of the complex weights for LMS and RLS algorithms.

Therefore, we conclude through Fig. 5 and Fig. 6 that the proposed IMUSIC method has the better resolution as compared to the other algorithms in the two aforementioned scenarios, especially in the second scenario in which the signals are coherent, where its effectiveness is evident.

4.2 Performance Evaluation of the Proposed Hybrid ABF Algorithm

This section presents simulations to stand on the best adaptive beamforming algorithm. The simulations analyze and compare the performance of popular blind ABF algorithms such as LCMV and MVDR, followed by a comparison of popular non-blind ABF algorithms such as LMS and RLS. Finally, the proposed hybrid ABF algorithm is compared to the most suitable blind ABF algorithm, which is MVDR, and the most suitable non-blind ABF algorithm, which is RLS.

The simulation carried out in Fig. 7 for the LCMV beamforming method response pattern reveals that the beamformer places limitations in the directions of the specified signals whilst minimizing interference signals along the angles 55 and 65 degrees. We note that the MVDR algorithm generates a null in the interfering signal direction at the angle of 60 degrees, while a flat response area around this interfering signal direction may be maintained by the LCMV algorithm. Thereafter, Comparing the response patterns of the LCMV and MVDR algorithms, we observe that the desired nulls could be better perceived using MVDR algorithm.

Then, we make a comparison between two non-blind adaptive beamforming algorithms, the RLS beamforming algorithm and the LMS algorithm, which are the most popular non-blind algorithm, using the antenna configuration and impinging signals discussed above.

In Fig. 8, we evaluate the average weights magnitude of the two aforementioned algorithms in terms of the iterations number. We discern that the LMS algorithm required a lot of iterations to get satisfactory convergence, which reached the convergence after 60 iterations. Moreover, The RLS algorithm attains convergence after about 15 iterations. Then, Figure 9 shows the output of the signal tracking by the LMS, and the RLS algorithms over $T = 100$ snapshots.

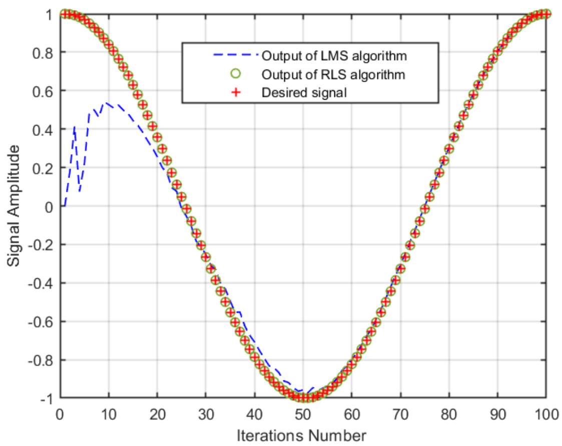

Fig. 9. Tracking of desired signal using LMS, RLS algorithms.

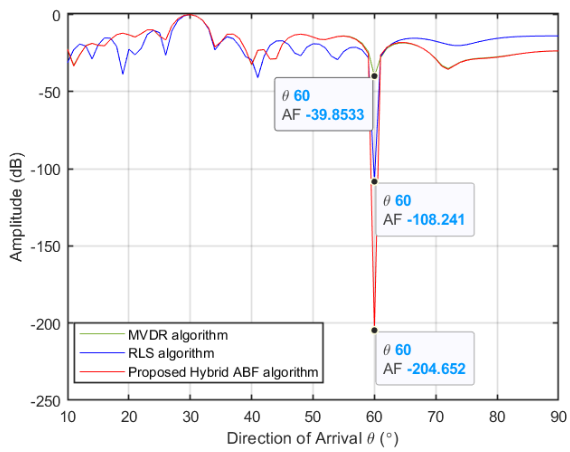

Fig. 10. Synthesized pattern using the proposed algorithm compared with the generated patterns using MVDR, RLS algorithms.

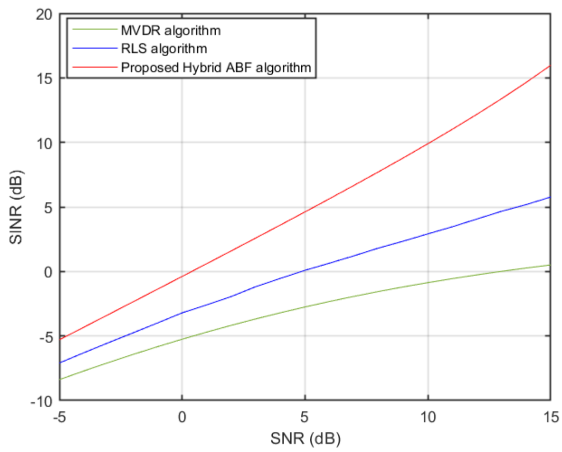

Fig. 11. Output SINR versus SNR of the desired signal using the proposed algorithm, the MVDR , and the RLS algorithms.

The simulation results in Fig. 9 show that the output of signal tracking using the RLS algorithm is similar to the desired signal. On the other hand, the results of the LMS algorithm converge to the desired signal values after 60 iterations. This gives preference to the RLS algorithm, which improves the convergence speed despite its higher computational complexity compared to the LMS algorithm.

Consider ULA with $M = 32$ antenna elements and $d_x = \frac{\lambda}{2}$, the desired signal direction is $\theta_d = 30°$, and the interfering signal direction is $\theta_\mathrm{I} = 60°$ with $SNR = 5$ dB. On the basis of the aforementioned parameters, we generated a simulation of the array pattern, as shown in Fig. 10, to evaluate the performance of the proposed algorithm compared to the MVDR and RLS algorithms in terms of SLLs at the directions of interfering signals.

According to the aforementioned information, the receiver knew the directions of the desired and interfering signals. The directions of the different incident signals were estimated using the proposed IMUSIC method, which enabled the receiver to accurately estimate the angles of arrival of the signals.

The proposed hybrid adaptive beamforming algorithm generates an accurate main beam steering toward the desired direction and an accurate pattern nulls placement at the directions of interfering signals. Thus, as indicated in Fig. 10 the proposed algorithm provides the lowest SSL at interfering signal direction, which is equal to -204.652 dB compared to the RLS algorithm with $SSL = -108.241$ dB and the MVDR algorithm with $SSL = -39.8533$ dB generated in the same direction. Therefore, the proposed algorithm provided the most severe and deepest null at the interfering signal direction. Furthermore, Figure 11 shows the output SINR of the proposed hybrid adaptive beamforming, RLS, and MVDR algorithms over SNR range from -5 to 15 dB. As the results obtained showed that the performance of the proposed algorithm is better compared to other algorithms.

The simulations carried out in Figs. 10 and 11, disclose that the proposed hybrid adaptive beamforming algorithm is the most efficient algorithm, which provides the highest SINR, and outperforms the MVDR and the RLS algorithms.

5. Conclusion

In this paper, a hybrid adaptive beamforming algorithm was proposed to enhance the SINR for mMIMO systems by accurately estimating the DoAs of incident signals at the array and directing the main beam towards the desired direction while creating deep nulls in the directions of interfering signals by adjusting the complex weights of the elements.

Initially, high-resolution direction-finding of incident signals at the elements of the antenna array is achieved using the improved MUSIC method, which effectively addresses the challenge of differentiating between coherent signals. The simulation results demonstrate the proposed method's effectiveness in estimating DoAs, providing good accuracy, and reducing noise by more than 40 dB, which outperforms other methods such as conventional MUSIC and MVDR that lose almost effectiveness under the same conditions.

Thereafter, a combination of a blind and a non-blind adaptive algorithms, MVDR and RLS successively, is employed to benefit from their merits and achieve efficient cancellation of interfering signals. Our simulation results reveal that the proposed ABF algorithm is superior to other ABF algorithms such as MVDR and RLS. Through several iterations to keep track of incident signals, the proposed algorithm creates a directive and accurate pattern in the desired direction and severe nulls towards the direction of the interfering signal. As a result, the proposed algorithm maximizes the SINR, providing more than 10 dB increase at high SNR regimes compared to other algorithms.

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