

Article

Mitigating Truncation Errors in Near-Field Phased Array Diagnostics Exploiting Steering Diversity

Mario Del Prete ^{1,2,*} , Raffaele Solimene ^{1,2} , Roberto Dima ^{1,2} , Antonio Cuccaro ¹ , Angela Dell'Aversano ^{1,2}  and Maria Antonia Maisto ^{1,2} 

- ¹ Department of Engineering, University of Campania "Luigi Vanvitelli", 81031 Aversa, Italy; raffaele.solimene@unicampania.it (R.S.); roberto.dima@unicampania.it (R.D.); angela.dell'avversano@unicampania.it (A.D.); mariaantoniamaisto@unicampania.it (M.A.M.)
² National Inter-University Consortium for Telecommunications (CNIT), 43124 Parma, Italy
* Correspondence: mario.delprete@unicampania.it

Abstract

This paper presents a novel technique for the diagnosis of faulty elements in phased array antennas. By exploiting the inherent steering diversity of phased arrays, the proposed approach overcomes the limitations imposed by truncation errors in the standard near-field Back-Transformation Method (BTM). Specifically, by reorganizing the spectra associated with each steering direction into a unified domain and leveraging data redundancy, the method effectively denoises the measurements and recovers a reliable bandwidth over the entire visible domain. Finally, an extensive Monte Carlo numerical analysis demonstrates the feasibility and enhanced accuracy of the proposed technique, highlighting its capability to achieve a high probability of detection with respect to the classical single-view approach.

Keywords: antenna diagnostics; fault detection; near-field measurements; CFAR; phased array antennas; steering diversity; truncation error

1. Introduction

Phased array systems are fundamental to a wide range of fields, including radar, satellite, automotive, and wireless communications [1–5]. However, due to the large number of radiating elements they typically integrate, the occurrence of faults that compromise the array's nominal functionality is inevitable. To successfully restore the array's performance [6] and guarantee that each element radiates according to its design specifications [7,8], defective elements must be localized using accurate diagnostic procedures [9–19]. To perform such diagnostics, near-field (NF) measurement techniques are often preferred over far-field (FF) approaches [20]. NF setups require significantly reduced spatial footprints, allowing operations to proceed within controlled environments (e.g., anechoic chambers) and effectively overcoming the logistical challenges associated with the extreme distance or mechanical rotation of large-scale arrays [21]. While NF scanning can be generally classified into planar [22], cylindrical [23], or spherical configurations [24], each offering distinct advantages depending on the antenna under test (AUT), this paper focuses specifically on planar scanning.

From a mathematical point of view, array diagnostics requires solving the inverse problem of recovering the complex excitation coefficients from the measured field. Since the nominal positions of the radiating elements are assumed to be known, this problem is typically cast as a linear inversion. To address this in planar configurations, the most



Academic Editor: Djurdj Budimir

Received: 22 June 2026

Revised: 25 July 2026

Accepted: 28 July 2026

Published: 1 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

common and classical approach is by far the Back-Transformation Method (BTM) [25]. By exploiting the plane-wave spectrum (PWS) representation, the BTM utilizes Fast Fourier Transform (FFT) for the efficient backward propagation of the measured field to the array aperture. Indeed, the FFT-based nature of the BTM guarantees unparalleled computational speed, making it highly attractive for the rapid diagnostics of arrays. Ideally, the radiated NF should be collected over an infinite plane. However, physical implementations are inherently restricted to scanning a finite measurement domain. Due to the truncated domain, the PWS is considered reliable exclusively within a restricted spectral region bounded by the valid angle (VA) [26] that is linked to the key parameters of the NF setup, namely, the observation domain extent, the antenna size, and their relative distance. Because of this VA restriction, the BTM suffers a significant degradation in spatial resolution. Therefore, isolated faults are generally hidden by the reconstruction of the correctly functioning elements adjacent to them. To limit the degrading effects of a finite measurement aperture and thus counteract the resulting loss in spatial resolution, several strategies have been investigated in the literature to improve diagnostic accuracy [27–29]. Some methods starting from NF data derive equivalent currents on a fictitious surface by directly inverting the pertinent integral equations [20]. Other techniques attempt to extrapolate the NF data outside the physical measurement aperture [30,31] or mathematically prolong the radiation pattern beyond the region where it is considered reliable according to the VA [32]. Furthermore, super-resolution techniques are frequently employed to enhance spatial resolution and overall reconstruction fidelity [33,34]. In this work, however, we follow a fundamentally different paradigm. Since the antenna under test is a phased array, we can rely on its inherent beam-steering capabilities to introduce an additional degree of data diversity, beyond the purely spatial one [35,36]. By systematically varying the electronic steering angle, near-field data are sequentially recorded across multiple scanning directions. This multidimensional acquisition intrinsically enriches the informational content available for diagnostics compared to conventional, single-view measurement setups. To strategically leverage this richer dataset and counteract the spatial truncation, rather than adopting more complex inversion schemes, and preserve the computational speed provided by the FFT, we modify the standard BTM algorithm. Specifically, the multi-view spatial spectra are mapped and fused onto a unified one-dimensional spectral domain. This joint processing achieves a significant spectral broadening, directly mitigating the valid angle limitation and restoring the degraded spatial resolution. Furthermore, the intrinsic spectral redundancy provided by different steering is successfully exploited to average out the background noise, yielding a powerful denoising effect. Finally, an extensive Monte Carlo analysis is presented to demonstrate that steering diversity significantly improves the overall reconstruction accuracy of the excitation coefficients compared to classical BTM. This enhancement translates directly into superior fault detection, as demonstrated through the use of an adaptive OS-CFAR detector adapted from the radar literature [37]. The remainder of this paper is organized as follows. Section 2 reviews the mathematical formulation of the classical BTM and the geometric limitations of single-view diagnostics. Section 3 introduces the multi-steering strategy, detailing the proposed approach. Section 4 presents the numerical validations, including the application of the OS-CFAR detector, to support the theoretical findings. Finally, concluding remarks are provided in Section 5.

2. Back-Transformation Method

Let us consider the measurement setup shown in Figure 1, consisting of a linear array of N radiating elements and the AUT, deployed over a rectilinear source domain $SD = [-X_s, X_s]$. The array elements are located at $\mathbf{r}_n = (x_n, 0, 0)$. The radiated field is collected at observation points $\mathbf{r}_0$ belonging to a finite linear observation domain $OD = [-X_0, X_0]$,

which is parallel to SD . The observation domain is situated in the near-field region, at a distance $z_0 > \lambda$ from the source array. Consequently, the radiated electric field vector can be expressed as

$$\mathbf{E}(\mathbf{r}_0) = \sum_{n=1}^N \mathbf{G}(\mathbf{r}_0, \mathbf{r}_n) c_n \quad (1)$$

where c_n is the n -th complex excitation coefficient of the array and

$$\mathbf{G}(\mathbf{r}_0, \mathbf{r}_n) = \frac{e^{-jk|\mathbf{r}_0 - \mathbf{r}_n|}}{|\mathbf{r}_0 - \mathbf{r}_n|} \mathbf{f}(\mathbf{r}_0, \mathbf{r}_n), \quad (2)$$

with $k = 2\pi/\lambda$ denoting the wavenumber and $\mathbf{f}(\mathbf{r}_0, \mathbf{r}_n)$ the element factor. In a realistic array, mutual coupling and finite-size effects are typically addressed by substituting the ideal element factor with the active embedded element pattern. Assuming that an ideal probe collects only a single field component tangential to the $x - y$ plane, Equation (1) reduces to the scalar relationship

$$E_t(\mathbf{r}_0) = \sum_{n=1}^N G_t(\mathbf{r}_0, \mathbf{r}_n) c_n, \quad (3)$$

where $E_t(\mathbf{r}_0)$ denotes either the x or y component of the field and $G_t(\mathbf{r}_0, \mathbf{r}_n)$ incorporates the corresponding component, $f_t(\mathbf{r}_0, \mathbf{r}_n)$, of the element factor. The array diagnostics problem aims to detect element failures by retrieving the excitation coefficients from near-field measurements acquired over OD . To achieve this goal, the principal and most widely adopted diagnostic approach in the literature for conventional (non-phased) arrays is the Back-Transformation Method (BTM), which relies on the plane-wave spectrum (PWS) expansion of the radiated field [25]. Let $\hat{E}_t(k_x, k_y, z_0)$ denote the plane-wave spectrum (PWS) of the tangential field at the measurement aperture $z = z_0$, where k_x and k_y are the spatial frequency variables. The spatial field distribution can be expressed as

$$E_t(x, y, z_0) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \hat{E}_t(k_x, k_y, z_0) e^{-j(k_x x + k_y y)} dk_x dk_y \quad (4)$$

where $k_z = \sqrt{k^2 - k_x^2 - k_y^2}$ is the longitudinal wavenumber. Since the spectrum propagates according to

$$\hat{E}_t(k_x, k_y, z_0) = \hat{E}_t(k_x, k_y, 0) e^{-jk_z z_0}, \quad (5)$$

the estimated excitation coefficients, $\hat{c}_n$, can be recovered by compensating for the propagation phase shift and the element factor. This yields

$$\hat{c}_n = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{k_z e^{jk_z z_0}}{f_t(k_x, k_y)} \hat{E}_t(k_x, k_y, z_0) e^{-j(k_x x_n + k_y y_n)} dk_x dk_y \quad (6)$$

As evident from (6), retrieving the excitation coefficients via the BTM requires computing two Fourier transformations: a forward transform to evaluate the field PWS and an inverse transform to achieve back-propagation. This procedure can be efficiently implemented using Fast Fourier Transform (FFT) algorithms, making the method highly attractive due to its low computational burden. In practical scenarios, as will be assumed throughout this paper, the field is sampled at $\lambda/2$ step. This sampling step effectively restricts the spectral band to the visible domain, filtering out the evanescent contributions. Crucially, restricting the spatial spectrum implicitly regularizes the inherently ill-posed inverse problem of retrieving the coefficients c_n from the field measurements. The ill-posedness is clearly visible in the back-propagation operator: the exponential term $e^{-jk_z z_0}$

diverges for non-visible spatial frequencies (i.e., $k_x^2 + k_y^2 > k^2$). However, it is important to remark that the estimate provided by (6) does not coincide with the optimal least-squares solution. This is a direct consequence of the finite measurement domain. Consequently, the PWS is affected by the so-called truncation error, meaning it is physically reliable only within a restricted spectral region $[-k_{\text{valid}}, k_{\text{valid}}]$. Geometrically, this region corresponds to a limited angular sector bounded by the valid angle (VA) [26]:

$$\theta_{\text{valid}} = \tan^{-1} \left(\frac{X_0 - X_s}{z_0} \right), \quad (7)$$

which depends on the extents of the observation and source domains, as well as the distance between them. To overcome the limitations imposed by a finite measurement aperture, the intrinsic flexibility of a phased array can be exploited. As detailed in the following section, by leveraging additional field measurements acquired at different steering angles, the proposed multi-steering approach effectively deals with truncation errors, significantly improving the overall current reconstruction.

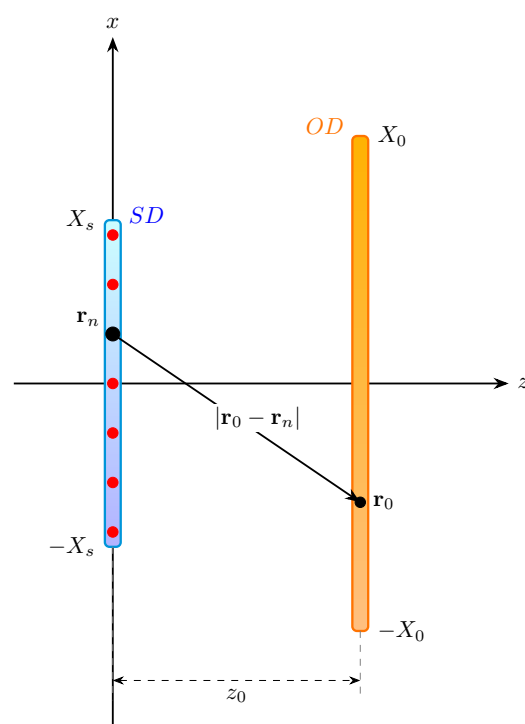


Figure 1. Geometry of the problem.

3. Steering Diversity-Based Diagnostic Framework

Let us examine the advantages offered when a phased array is under test with respect to a conventional array configuration. A phased array allows the electronic steering of the main beam across the field of view, introducing an additional degree of data diversity, beyond the purely spatial one. This steering diversity suggests that the diagnostic stage can in principle benefit from a richer dataset than what a single fixed configuration would provide. In this configuration, the radiated field is collected on OD at M spatial locations for L distinct steering angles.

The steering angles span the angular domain $AD = [-\theta_A, \theta_A]$; thus, for the l -th angle θ_l , the field takes the form

$$E_t(\mathbf{r}_0, \theta_l) = \sum_{n=1}^N G_t(\mathbf{r}_0, \mathbf{r}_n) e^{jk_{x_n} \sin \theta_l} c_n \quad (8)$$

Basically, each steering configuration thus yields a measurement vector of length M , and stacking the L such vectors column-wise produces the data matrix $\mathbf{E}_t \in \mathbb{C}^{M \times L}$. In principle, the standard BTM could be independently applied to each column of the data matrix, as each corresponds to a single isolated view. While the steering phase term simply translates the main beam of the PWS for each view, the physical measurement geometry remains unchanged; consequently, every single view inherently suffers from the exact same truncation error. Therefore, a processing approach that jointly considers all spectra is necessary to leverage the additional information provided by the steering diversity. To this end, we first compute the PWS for each column of the data matrix and compensate for the element factor. Note that at this stage, realistic effects, such as mutual coupling and eventually steering-dependent effects, can be taken into account within the active element pattern and properly compensated for. Moreover, if required, standard spectral probe-compensation techniques can be seamlessly integrated at this stage. By dividing the measured spectrum by the known plane-wave spectrum of the probe, the field is equalized before applying our multi-view mapping, without altering the core algorithm. The resulting vectors can then be arranged into a matrix $H \in \mathbb{C}^{P \times L}$, whose (p, l) -th entry is given by

$$H(k_{x_p}, k_{s_l}) = \sum_{n=1}^N c_n e^{j(k_{x_p} - k_{s_l})x_n} = H(k_{x_p} - k_{s_l}) \quad (9)$$

where P represents the number of points over which the variable $k_x \in [-k, k]$ is discretized and $k_{s_l} = k \sin \theta_l$. Observing the right-hand side of (9), it is evident that H depends on the difference $k_{x_p} - k_{s_l}$. By introducing the new variable $u(p, l) = k_{x_p} - k_{s_l}$, we can rewrite (9) for each value u_q as

$$H(u_q) = \sum_{n=1}^N c_n e^{ju_q x_n}, \quad (10)$$

where explicit dependencies are omitted for notational simplicity. It can be observed that the right-hand side resembles a one-dimensional Fourier transform in the u -variable. Yet, from a dimensional standpoint, this 1D transform is linked to a matrix, representing a 2D dataset. Consequently, we need to map the 2D data onto a 1D structure, enabling the reconstruction of the coefficients through an inverse Fourier transform in the u -domain. To perform this mapping, we note that since the l -th steering angle shifts the PWS by k_{s_l} , the information obtained in the u -variable covers the spectral domain ranging from $-k - k_{s_l}$ to $k - k_{s_l}$. This suggests that the PWS data associated with different steering angles overlap across their corresponding intervals in the u -domain. Consequently, there exist sets

$$I_q = \{(p, l) : k_{x_p} - k_{s_l} = u_q\} \quad (11)$$

with a cardinality $N_q > 1$. This implies that multiple (p, l) pairs map to the same value u_q , resulting in inherent data redundancy. As is well established in the literature, such redundancy can be leveraged to mitigate the effects of noise [38]. In particular, we can simultaneously achieve the desired 1D mapping and a denoising effect by summing the data points corresponding to the same u_q and averaging over the number of redundant entries, N_q , as follows:

$$H_{1D}(u_q) = \frac{1}{N_q} \sum_{p, l \in I_q} H(k_{x_p} - k_{s_l}), \quad (12)$$

where H_{1D} is the 1D spectrum in the u variable that we are looking for. Naturally, the extent of this denoising effect depends on the number of overlaps, which is tied to the number of steering angles and, in turn, determined by the available phase shifter states. In addition to this noise reduction, we achieve a significant broadening of the spectral range

with respect to the visible domain as the variable u spans the interval $[-k - k_{s_L}, k + k_{s_L}]$. In principle, this spectral expansion could lead to an improvement in resolution compared to the single-view case. However, from a practical diagnostic standpoint, our interest is exclusively focused on the visible region, corresponding to the spectral support $u \in [-k, k]$. Unfortunately, the main drawback of the proposed overlapping procedure is that it combines each individual spectrum over the visible region, thereby including data from beyond the valid angle. Merging trustworthy spectral data with unreliable portions leads to a negligible improvement in overall performance. To overcome this problem, the spectrum associated with each single view must be filtered to retain only the valid angle region before computing the average. Accordingly, the equation is modified as

$$H_{W_{1D}}(u_q) = \frac{\sum_{p \in I_q} H(k_{x_p} - k_{s_l}) W(p)}{\sum_{p \in I_q} W(p)}, \quad (13)$$

where $W(p)$ is a binary window function used to filter out the spectral components falling outside the valid angle region. It is defined as

$$W(p) = \begin{cases} 1, & \text{if } |k_{x_p}| \leq k_{\text{valid}} \\ 0, & \text{otherwise} \end{cases}$$

Finally, by restricting the spectrum in the u -domain to the interval $[-k, k]$, the coefficients c_n can be retrieved by computing the inverse Fourier transform of

$$H_{W_{1D}}(u_q) = \sum_{n=1}^N c_n e^{j u_q x_n}. \quad (14)$$

The flowchart in Figure 2 summarizes the steps of the proposed algorithm. A few remarks are in order. First, the maximum steering angle is inherently limited by the valid angle. Indeed, steering beyond this threshold would shift the main lobe of the PWS outside the $[-k_{\text{valid}}, k_{\text{valid}}]$ region, causing it to be truncated when the window is applied. Consequently, by combining the valid angle restriction with the maximum permissible steering, the widest achievable spectral band spans from $-2k_{\text{valid}}$ to $2k_{\text{valid}}$. Thus, to successfully cover the entire $[-k, k]$ interval, the system configuration must guarantee a k_{valid} of at least $k/2$. However, highly restricted measurement setups (i.e., $X_o \approx X_s$) can lead to geometries where $k_{\text{valid}} < k/2$. While such extreme edge cases are generally avoided in standard near-field acquisitions, a robust diagnostic tool must still account for them. In these restricted scenarios, reaching full coverage of the $[-k, k]$ spectrum strictly requires a controlled trade-off, which inherently makes the operating condition sub-optimal.

Specifically, to overcome the geometric bottleneck, we enforce a maximum steering of $\pi/6$ (corresponding to $k/2$) and redefine the window function W as follows:

$$W(p) = \begin{cases} 1, & \text{if } |k_{x_p}| \leq \max(k/2, k_{\text{valid}}) \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

Although relaxing the rigorous valid-angle bound inevitably introduces a slight truncation error, this conservative strategy ensures that the reconstructed spectrum remains reliable over a significantly broader region compared to the standard single-view case.

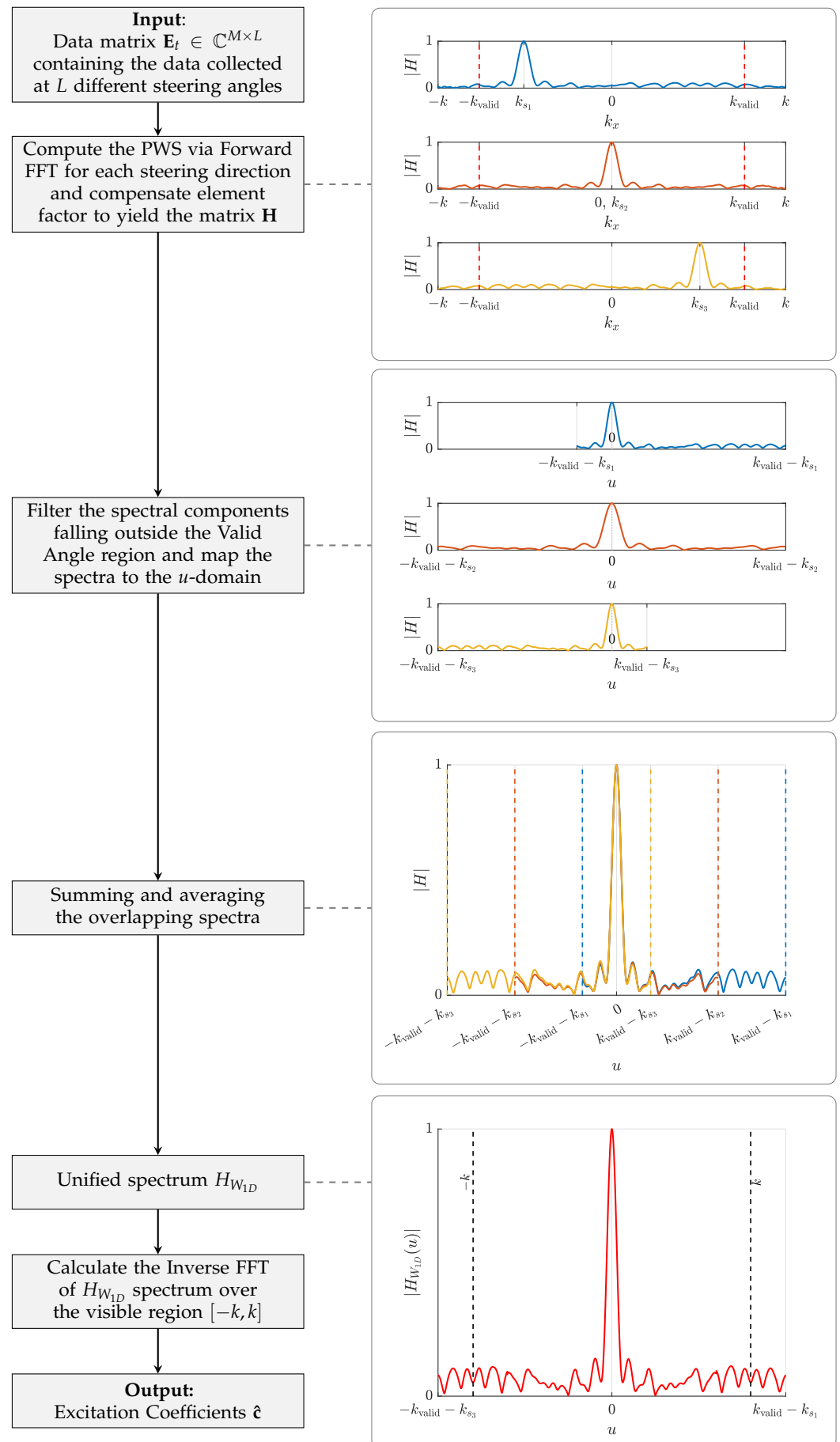


Figure 2. Flowchart of the proposed steering diversity-based diagnostic framework.

Second, in realistic scenarios, phase-shifter states deviate from their nominal values due to hardware non-idealities, which introduce both amplitude imbalances and phase uncertainties. The amplitude imbalances act as uncorrelated amplitude noise across the L different views. By design, our algorithm straightforwardly addresses this issue, as the averaging performed over the redundant overlapping regions effectively mitigates these amplitude deviations. Conversely, phase deviations present a more challenging issue. Although the nominal values of the shift parameters k_{s_l} are known, actual phase errors manifest as a global beam squint, causing the plane wave spectrum (PWS) to shift to a non-nominal position. If the nominal shift parameters were blindly applied during the mapping phase in the u -domain, the spectral maxima associated with each PWS would misalign. This would inevitably lead to an incoherent summation of the spectra and significant reconstruction errors. However, the proposed framework is intrinsically resilient to these phase inaccuracies. Since each shifted PWS is computed directly from the measured near-field data, the true steering direction of each spectrum corresponds to its global maximum. Therefore, the actual k_{s_l} can be extracted directly from the measured data by locating these spectral peaks. In this regard, the reorganization of the spectra in the u -domain acts as a self-calibrating, data-driven approach. By utilizing these empirically derived maxima rather than the nominal phase-shifter states, the spectral reorganization achieves perfect alignment. Finally, regarding computational complexity, the overall burden depends primarily on the number of steering angles. Specifically, the proposed procedure requires $L + 1$ Fourier transforms: L forward FFTs to compute the shifted spectra, followed by a single inverse FFT (IFFT) to retrieve the final excitation coefficients.

4. Numerical Results

This section presents a numerical analysis to evaluate the performance of the proposed diagnostic approach. As a first representative example, we consider a linear phased array of $N = 41$ x -oriented dipoles. The array is uniformly spaced at $\lambda/2$ over a support length of $X_s = 10\lambda$. The radiated field is collected in the observation domain (OD) over $M = 73$ measurement points, spanning a length of $X_0 = 18\lambda$ at a distance of $z_0 = 7\lambda$. In this configuration, the valid angle is 48° , which corresponds to $k_{\text{valid}} = 0.75k$. Therefore, to ensure reliable spectral coverage across the entire visible region, a maximum steering angle of at least 14° ($k_{s_L} = 0.25k$) is required and was thus selected. Beam steering is achieved using a 4-bit phase shifter. Among the possible 17 states, $L = 5$ steering angles are required to cover the desired steering range $AD = [-14^\circ, 14^\circ]$. In this scenario, the excitation coefficients follow a Taylor taper with a Side Lobe Level (SLL) of -30 dB and $\bar{n} = 4$. Among these, we assume that $N_{\text{fault}} = 5$ elements are completely turned off. Finally, additive White Gaussian Noise (AWGN) is introduced to the data, setting a Signal-to-Noise Ratio (SNR) of 15 dB. Under these conditions, we compare the reconstructed current distributions obtained using the standard BTM approach (single view, specifically operating in the broadside unsteered configuration) with those retrieved by the proposed strategy. Figure 3 shows the nominal excitation coefficients (panel a) alongside those reconstructed using both the classical BTM (panel b) and the proposed approach (panel c). As can be observed, owing to the limited spatial resolution of the standard BTM, the reconstructed amplitudes of certain faulty elements (indicated by red asterisks) erroneously exceed those of the functioning, low-excitation elements situated at the array edges. Consequently, these faults are not correctly identified, leading to false positives. In contrast, this masking effect is successfully mitigated when applying steering diversity. The current amplitudes are accurately reconstructed, allowing for the straightforward identification of faulty elements.

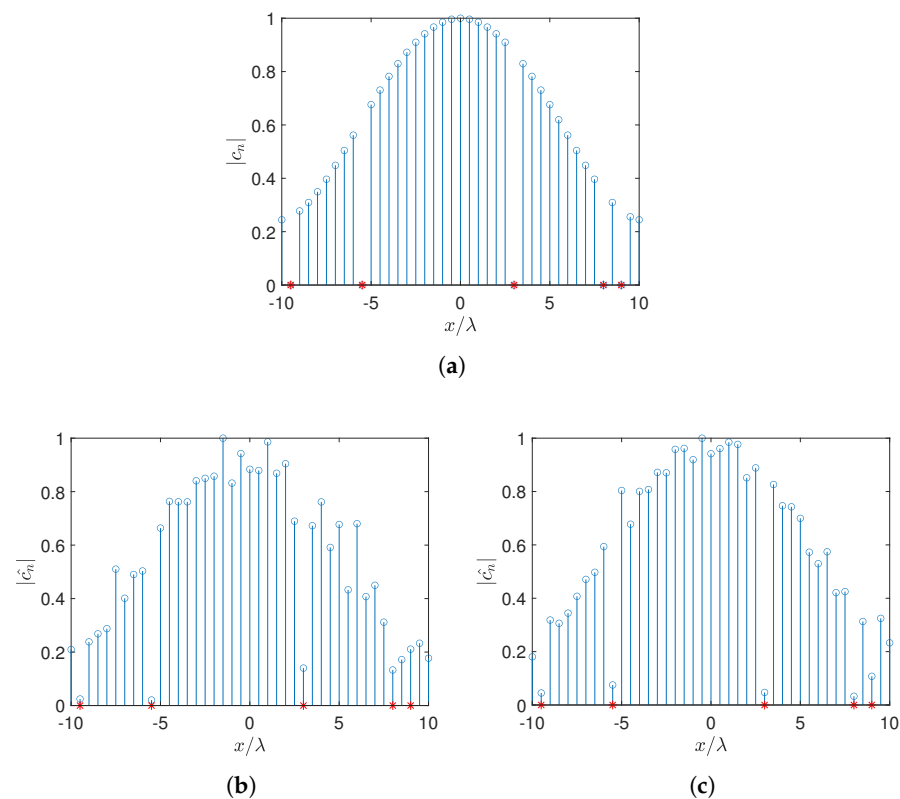


Figure 3. Comparison of the normalized array excitation coefficients: (a) nominal distribution, (b) classical BTM reconstructions, and (c) reconstructions via the proposed approach. The array consists of $N = 41$ x -directed dipoles with a $\lambda/2$ spacing over a support $X_s = 10\lambda$, and the nominal state follows a Taylor distribution with an SLL of 30 dB and $\bar{n} = 4$.

This representative example highlights the two-fold advantage of the proposed strategy. First, acquiring the minimum required number of steering angles guarantees full spectral coverage; this effectively mitigates truncation errors and restores the spatial resolution needed to pinpoint faults that the single-view approach can miss. Second, the intrinsic data redundancy provided by the multiple overlapping views acts as a powerful denoising mechanism, significantly reducing the impact of noise and yielding a highly accurate reconstruction of the excitation coefficients. To thoroughly highlight how the proposed approach effectively mitigates the truncation error compared to the classical BTM, and consequently enhance the reconstruction accuracy, a set of Monte Carlo analyses were conducted. In the first analysis, the previously defined array setup and observation distance, z_0 , were kept constant. Consequently, the truncation error depended solely on the measurement domain extent, which was set to $X_0 \in \{1.2X_s, 1.4X_s, 1.6X_s, 1.8X_s, 2X_s\}$. For a fair comparison, for all the values of X_0 , the maximum steering angle was fixed at $\pi/6$ (yielding $L = 9$ steering angles), a value chosen to guarantee reliable coverage of the entire visible region in all cases. It is worth noting that the value $X_0 = 1.2X_s$ (yielding $k_{\text{valid}} = 0.272 < k/2$) was deliberately chosen to test the algorithm's performance under suboptimal conditions.

For each measurement aperture size, the Mean Square Reconstruction Error (MSRE) was evaluated, defined as

$$\text{MSRE} = \frac{1}{N_{\text{trial}}} \sum_{i=1}^{N_{\text{trial}}} \|\mathbf{c}(i) - \hat{\mathbf{c}}(i)\|, \quad (16)$$

where $\|\cdot\|$ represents the euclidean norm while $\mathbf{c}(i)$ and $\hat{\mathbf{c}}(i)$ denote the actual and reconstructed excitation vectors during the i -th iteration, respectively. The error was computed over $N_{\text{trial}} = 1000$ independent Monte Carlo iterations.

At each iteration, the positions of $N_{\text{fault}} = 9$ faulty elements were randomly changed. Rather than assuming a completely turned off fault, the analysis took into account both amplitude and phase defects. Consequently, the actual excitation coefficients were modeled as

$$c_n = c_n^{\text{ref}}(a_n e^{j\varphi_n}), \quad (17)$$

where c_n^{ref} represents the nominal excitation coefficient and a_n and φ_n the amplitude and phase defect respectively. The latter were generated according to

$$a_n = 0.2\mathcal{U}(0, 1) \quad (18)$$

and

$$\varphi_n = -\frac{\pi}{6} + \frac{\pi}{3}\mathcal{U}(0, 1), \quad (19)$$

where $\mathcal{U}(0, 1)$ denotes a uniformly distributed random variable over the interval $[0, 1]$.

$$E_t(\mathbf{r}_0, \theta_l) = \sum_{n=1}^N G_t(\mathbf{r}_0, \mathbf{r}_n) g_l e^{j(k_{s,l} + \lambda_l)x_n} c_n.$$

To simulate a realistic phase shifter, each nominal state was affected by an additive phase uncertainty ϕ_l and an multiplicative amplitude factor g_l , defined as

$$\phi_l = -\frac{\pi}{60} + \frac{\pi}{30}\mathcal{U}(0, 1), \quad g_l = 0.95 + 0.10\mathcal{U}(0, 1)$$

The analysis was repeated across different noise levels: $\text{SNR} \in \{10, 15, 20\}$ dB. The MSREs obtained through the Monte Carlo analysis as a function of the ratio X_0/X_s are summarized in Table 1, while a visual representation of this behavior is provided in Figure 4. As expected, for a fixed SNR, the MSRE decreases for both procedures as the ratio X_0/X_s increases, owing to the reduction of the truncation error. Furthermore, for a given X_0/X_s ratio, the reconstruction error naturally decreases as the SNR increases. Most importantly, as can be observed, the MSRE achieved by the proposed approach is consistently lower than that of the standard BTM across the entire evaluated range of X_0/X_s .

Table 1. Reconstruction performance comparison in terms of MSRE between the proposed approach and the standard BTM as a function of X_0/X_s .

SNR (dB)	X_0/X_s	MSRE (dB)	
		Proposed Approach	Standard BTM
10	1.2	−15.08	−9.58
	1.4	−15.64	−9.83
	1.6	−17.47	−9.98
	1.8	−18.26	−10.21
	2.0	−18.63	−10.33
15	1.2	−19.51	−12.59
	1.4	−20.23	−13.11
	1.6	−22.17	−13.49
	1.8	−22.93	−13.83
	2.0	−23.29	−14.08

Table 1. Cont.

SNR (dB)	X_0/X_s	MSRE (dB)	
		Proposed Approach	Standard BTM
20	1.2	−23.52	−14.77
	1.4	−24.61	−15.55
	1.6	−26.54	−16.09
	1.8	−27.11	−16.53
	2.0	−27.21	−16.94

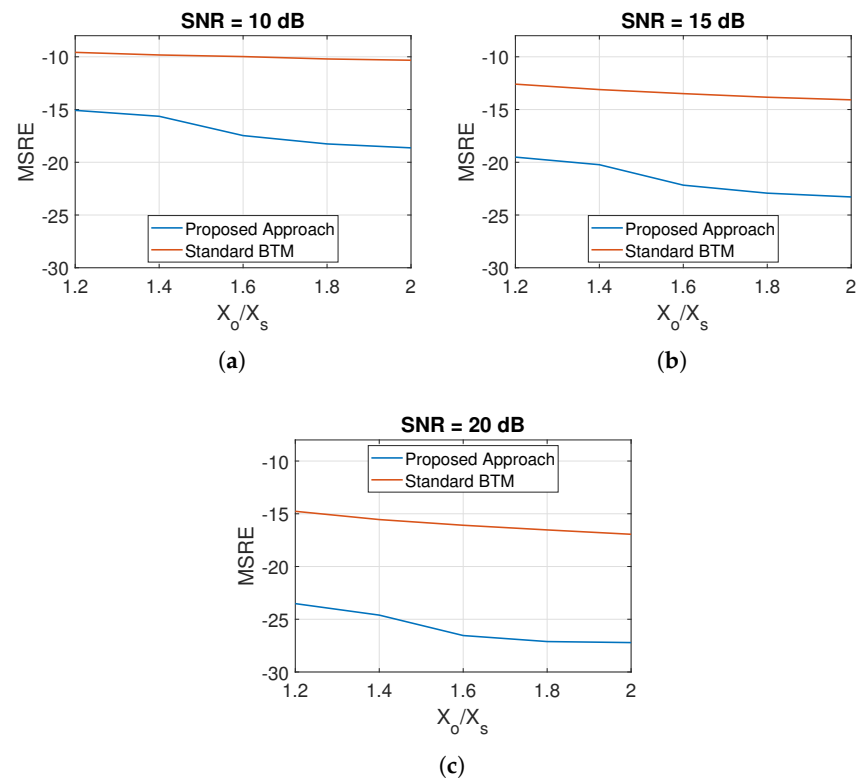


Figure 4. Monte Carlo analysis results: Mean Square Reconstruction Error (MSRE) as a function of the ratio X_0/X_s . The performance of the proposed approach is compared against the classical BTM at different Signal-to-Noise Ratios (SNRs): (a) 10 dB, (b) 15 dB, and (c) 20 dB.

This holds true even under the suboptimal condition of $X_0 = 1.2X_s$, where, for SNR values of 10 and 20, the performance is practically identical to the borderline case of $X_0 = 1.4X_s$, in which $k_{\text{valid}} = k/2$.

This demonstrates that introducing steering diversity significantly improves the reconstruction of the entire set of excitation coefficients. However, it is crucial to verify whether this enhanced accuracy actually translates into better fault identification. To this end, it is necessary to assess the procedure's capability to correctly detect faults while minimizing false alarms.

Consequently, using the same set of Monte Carlo simulations, in addition to the MSRE, the probability of false alarm (PFA) and the probability of detection (PD) are evaluated. The latter are defined as

$$\text{PFA} = \frac{1}{N_{\text{trial}}} \sum_{i=1}^{N_{\text{trial}}} \frac{FP(i)}{N - N_{\text{fault}}} \quad (20)$$

and

$$PD = \frac{1}{N_{\text{trial}}} \sum_{i=1}^{N_{\text{trial}}} \frac{FD(i)}{N_{\text{fault}}}, \quad (21)$$

where $FP(i)$ and $FD(i)$ denote the number of false positives and correctly detected faults during the i -th iteration, respectively.

A fundamental step in computing PD and PFA is establishing a robust criterion to determine whether a reconstructed coefficient corresponds to a faulty element. To this end, we can leverage the results presented in [39].

Since the fault-free reference array (the “golden” array) is typically known, it is possible to compute a difference array to highlight peak-like discrepancies. Denoting the reconstructing operator by BTM (regardless of whether steering diversity is exploited) as $\mathcal{B}$, returning the reconstructed coefficients $\hat{\mathbf{c}}$, this array is defined as

$$\Delta \mathbf{c} = \mathcal{B}(E_t - E_t^G) = [\hat{\mathbf{c}} - \mathbf{c}_{\text{proj}}] \quad (22)$$

where E_t^G is the field radiated by the reference array and the projected reference current, $\mathbf{c}_{\text{proj}}$, is computed as

$$\mathbf{c}_{\text{proj}} = \mathcal{B}(E_t^G).$$

It is worth noting that to know the field radiated by the golden array is a common baseline widely adopted in most diagnostic approaches [40–46]. By formulating the difference array in terms of the measured reference field, manufacturing tolerances, element-to-element variations, and static amplitude/phase deviations are intrinsically accounted for in both reconstructions ($\hat{\mathbf{c}}$ and $\mathbf{c}_{\text{proj}}$) and naturally cancel out. Once the difference array is evaluated, the n -th element is faulty if $|\Delta c_n|$ exceeds a detection threshold A_{th} . However, as discussed in [39], applying a fixed global threshold proves highly ineffective, particularly in the presence of tapered current profiles.

Instead, because the projection operation successfully cancels out the contributions of the correctly functioning elements, the residual energy in the difference array consists solely of the faults and background measurement noise. By exploiting this property, the local noise power can be reliably estimated to maintain a constant probability of false alarm (PFA). To this end, we adopt an adaptive thresholding approach based on the Order Statistic CFAR (OS-CFAR). This algorithm operates by sliding a local observation window across the difference array. For each element evaluated, designated as the Cell Under Test (CUT), the algorithm considers a set of N_c adjacent training cells. Crucially, these training cells are separated from the CUT by N_g guard cells symmetrically placed on each side. These guard cells are excluded from the threshold calculation to prevent the spatial footprint of a faulty element from contaminating the local noise estimate. Once this protective margin is established, the algorithm processes the remaining valid window by sorting the amplitude values of the training cells in ascending order. Rather than averaging these values as in CA-CFAR, the OS-CFAR selects the p -th value of this sorted list (e.g., the median or a higher percentile) to represent the noise background. The adaptive threshold A_{th} is finally obtained by multiplying this p -th selected value by a scaling factor α , which is numerically determined to achieve the desired PFA according to

$$PFA = \prod_{i=0}^{k-1} \frac{N_c - i}{N_c - i + \alpha}$$

By relying on order statistics rather than local averages, the OS-CFAR provides robust detection even in multi-fault scenarios, effectively avoiding the masking effect caused by closely spaced defective elements. In the following numerical validations, the OS-CFAR

detector is configured using $N_c = 6$ training cells, $N_g = 1$ guard cell, the order statistic p set to the median value, and a target false alarm rate of $PFA_d = 10^{-3}$.

With the threshold selection criterion established, the Monte Carlo analysis results in terms of PD and PFA are summarized in Table 2.

Table 2. Detection performance comparison (PD and PFA) between the proposed approach and the standard BTM for different values of X_0/X_s .

SNR (dB)	X_0/X_s	P_D		$P_{FA} (\times 10^{-3})$	
		Proposed Approach	BTM	Proposed Approach	BTM
10	1.2	0.6710	0.1176	0.504	0.596
	1.4	0.7211	0.1472	0.383	0.536
	1.6	0.7906	0.1628	0.600	0.646
	1.8	0.8056	0.1666	0.660	0.711
	2.0	0.8257	0.1907	0.626	0.649
15	1.2	0.8475	0.3572	0.617	0.879
	1.4	0.8905	0.4141	0.273	0.650
	1.6	0.9446	0.4764	0.693	0.875
	1.8	0.9668	0.5061	0.404	0.671
	2.0	0.9653	0.5264	0.489	0.646
20	1.2	0.9610	0.5597	1.012	1.127
	1.4	0.9924	0.6349	0.555	0.859
	1.6	0.9990	0.6851	0.491	0.851
	1.8	0.9996	0.7192	0.437	0.812
	2.0	0.9993	0.7502	0.189	0.432

Furthermore, the PD behavior as a function of the X_0/X_s ratio, for both the proposed approach and the classical BTM, is depicted in Figure 5. To indicate the statistical reliability of the estimates, the figure includes error bars representing the exact 95% binomial confidence intervals derived from the independent Monte Carlo trials. These bounds show the range within which the true probability values are expected to fall with 95% certainty. Since these error margins are remarkably narrow, particularly for the proposed approach, an inset is added for clearer visualization. Notably, the lack of overlap between the confidence intervals of the two methods across all the evaluated scenarios statistically confirms that the performance improvement achieved by the proposed approach is significant and not due to random fluctuations in the Monte Carlo trials.

Specifically, for both methods, the PD increases as the SNR and observation domain size increase, since the latter expands the spectral region associated with the valid angle and reduces truncation errors.

However, unlike the classical approach, the introduction of steering diversity effectively mitigates these truncation errors even for low observation-to-source domain ratios (X_0/X_s), as evidenced by the fact that the PD of the proposed method consistently exceeds that of the standard case.

In particular, at an SNR of 15 dB and $X_0/X_s = 1.4$, the proposed approach already yields a PD of 90%, while at 20 dB for the same domain ratio, the detection probability is close to 100%. In contrast, the standard BTM only achieves an acceptable PD of approximately 75% under the most favorable tested conditions (SNR = 20 dB and $X_0/X_s = 2$). The proposed approach maintains good performance even at 10 dB, a particularly demanding SNR level for diagnostic applications, where higher values are typically expected, reaching a PD of 82% at $X_0/X_s = 2$, with performance improving significantly at 15 dB and above.

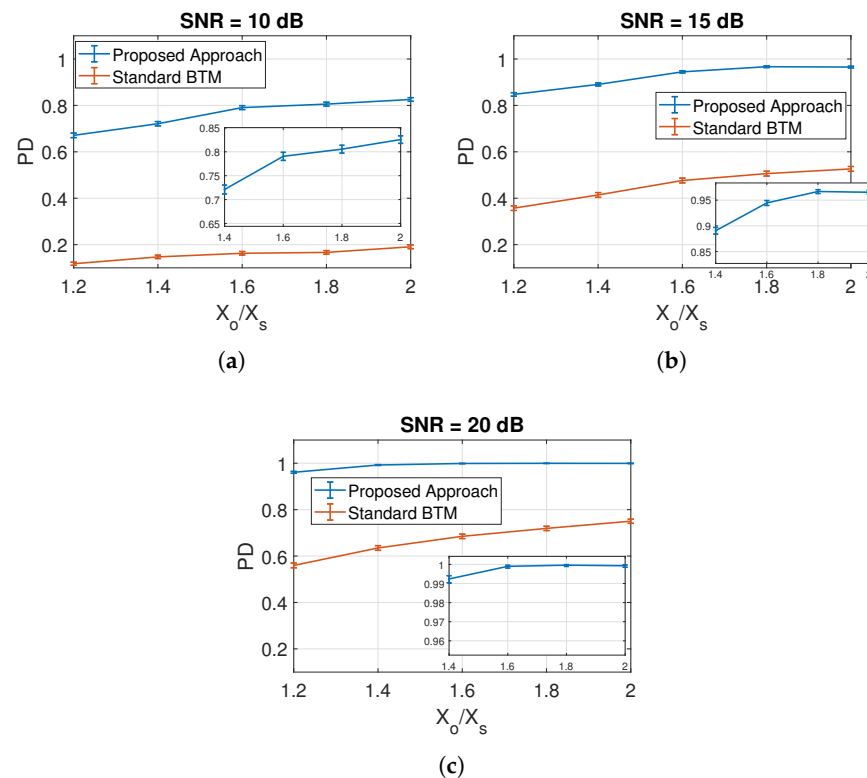


Figure 5. Monte Carlo analysis results: probability of detection (PD) as a function of the ratio X_0/X_s . The performance of the proposed multi-view approach is compared against the classical BTM at different Signal-to-Noise Ratios (SNRs): (a) 10 dB, (b) 15 dB, and (c) 20 dB.

Conversely, at lower SNRs of 10 dB and 15 dB, the standard BTM proves to be largely unreliable in terms of detection probability, regardless of the measurement domain size.

Moving to the comparison in terms of the probability of false alarm (PFA), the adopted OS-CFAR detector proves to be highly effective. As shown in Table 2 and Figure 6, both methods successfully maintain the probability of false alarm (PFA) around the nominal design value across all tested scenarios.

This behavior perfectly aligns with theoretical expectations, as the intrinsic purpose of the CFAR architecture is precisely to dynamically adjust the detection threshold to guarantee a constant false alarm rate, irrespective of the applied reconstruction algorithm.

Furthermore, although the PFA of the proposed approach is consistently slightly lower than that of the standard BTM, an analysis of the 95% confidence intervals reveals a significant overlap between the two methods, indicating that this difference is marginal.

This confirms the highly positive outcome that the proposed approach achieves its substantial gains in detection probability (PD) without incurring any penalty in false alarms, which remain securely constrained by the CFAR detector for both techniques.

As a final validation step, we investigated the behavior of the proposed approach with respect to data redundancy, which is governed by the number of steering angles. To this end, we conducted an additional Monte Carlo analysis. The array geometry was kept identical to the representative example, with a fixed measurement domain of $X_0 = 1.8X_s$ at $z_0 = 7\lambda$. To investigate the effects of different levels of spectral redundancy, the number of views varied within $L \in \{5, 7, 9, 11, 13\}$. The lower bound ($L = 5$) corresponded to the 14° steering angle required for minimum visible domain coverage, while the upper bound ($L = 13$) represented the maximum steering achievable within the valid angle using a 4-bit phase shifter.

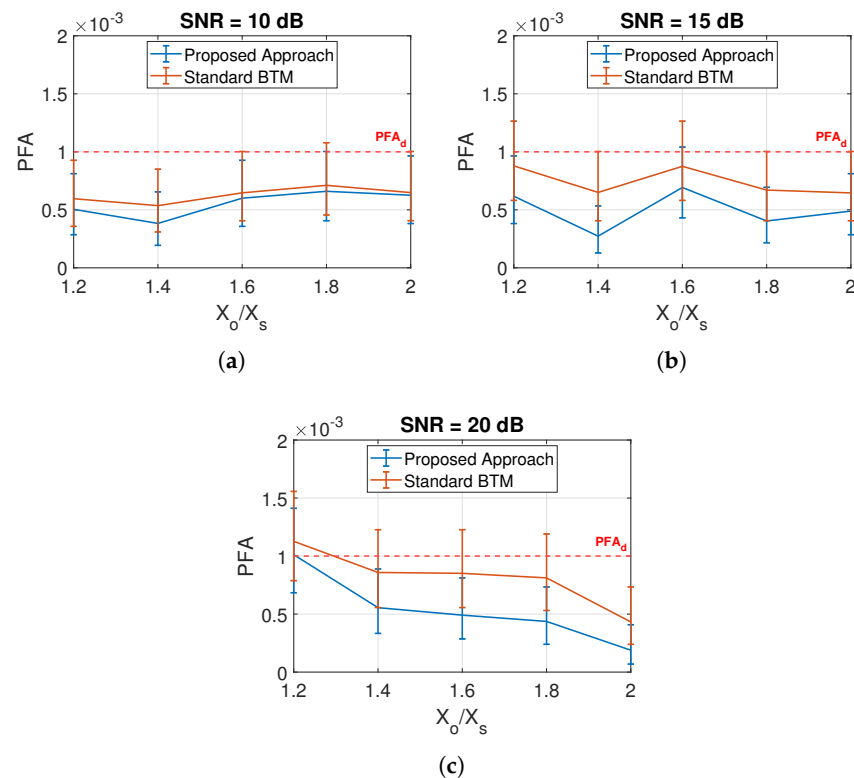


Figure 6. Probability of false alarm (PFA) versus ratio X_0/X_s evaluated through Monte Carlo simulations. The curves compare the proposed multi-steering approach against the classical BTM across three noise levels: (a) SNR = 10 dB, (b) SNR = 15 dB, and (c) SNR = 20 dB.

The MSRE, PD, and PFA metrics were computed over $N_{trial} = 1000$ independent trials. The number of faults, their spatial distribution, the amplitude and phase errors, and the phase shifter state error all varied within the same ranges as before. Additionally, the OS-CFAR detector parameters remained unchanged from the previous Monte Carlo setup. This analysis was repeated for $SNR \in \{10, 15, 20\}$ dB.

The obtained MSREs are shown in the Table 3, while Figure 7a illustrates their behavior as a function of the number of steering angles for different SNRs.

Table 3. Performance of the proposed approach across varying SNRs and steering angles.

SNR (dB)	L	MSRE (dB)	PD	PFA ($\times 10^{-3}$)
10	5	−14.63	0.6186	0.436
	7	−16.76	0.7618	0.588
	9	−18.19	0.8121	0.538
	11	−19.49	0.8617	0.469
	13	−20.43	0.9027	0.635
15	5	−19.11	0.8351	0.452
	7	−21.34	0.9242	0.503
	9	−22.93	0.9613	0.587
	11	−24.22	0.9835	0.408
	13	−25.23	0.9934	0.399
20	5	−23.20	0.9803	0.654
	7	−25.44	0.9974	0.411
	9	−27.16	0.9994	0.411
	11	−28.64	0.9998	0.537
	13	−29.72	0.9999	0.600

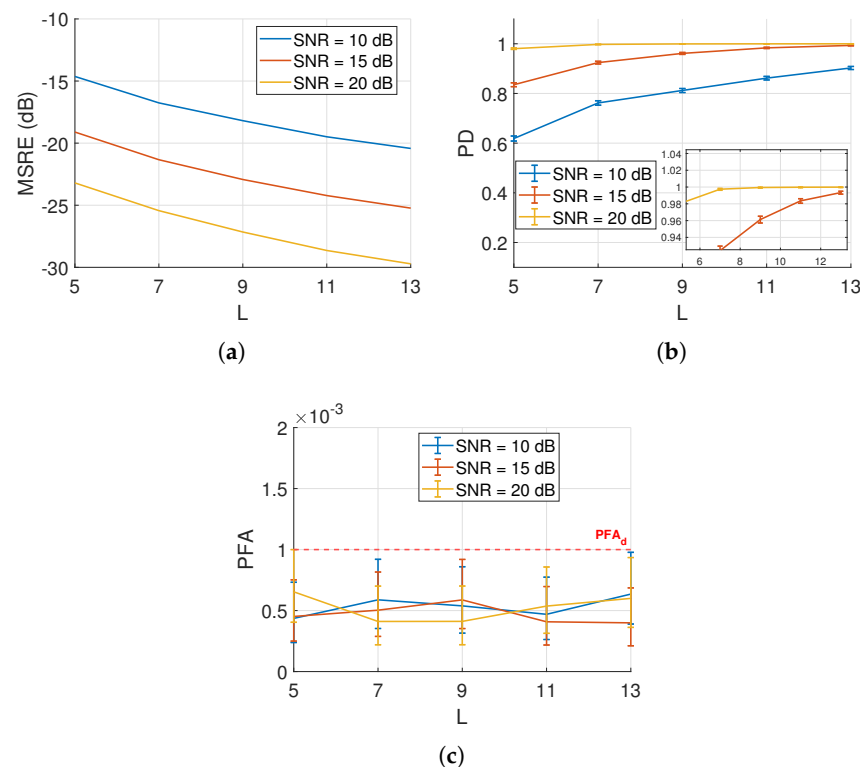


Figure 7. Effect of spectral redundancy on diagnostic performance evaluated via Monte Carlo analysis: (a) Mean Square Reconstruction Error, (b) probability of detection (PD), and (c) probability of false alarm (PFA) versus the number of steering views (L) at different SNR levels.

The observed trend is clear and perfectly aligns with our expectations. The MSRE decreases as the SNR increases, and most notably as the number of steering angles grows. This occurs because a higher number of steering directions results in a greater number of overlapping spectra, which, in turn, significantly strengthens the denoising effect. Shifting our focus to the fault detection performance, the results are presented in the Table 3, while Figure 7b illustrates the behavior of the probability of detection with respect to the number of views L for different SNR levels, alongside the corresponding 95% confidence intervals. As can be observed, particularly for low SNRs, increasing the number of steering leads to a significant enhancement of the probability of detection. In fact, at SNR = 10 dB, expanding the dataset from 5 to 13 steering yields a remarkable 40% increase in PD. For higher SNRs, the required number of steering angles decreases: at 15 dB, just nine steering angles are sufficient to approach a $PD \approx 1$, while at 20 dB, near-perfect detection is achieved with a low number of steering angles.

Observing the probability of false alarm in Figure 7c, it consistently remains below the design value. Here too, the overlapping confidence intervals lead to the same conclusions drawn in the previous analysis. These findings perfectly align with our theoretical expectations: exploiting spectral redundancy provides an intrinsic denoising effect, which drastically improves diagnostic performance, especially under severe noise conditions.

5. Conclusions

In this paper, the problem of linear phased antenna diagnostics from near-field measurements was addressed. The introduction of steering diversity mitigated the truncation errors caused by the finite measurement domain, which strictly limits the reliable spectral bandwidth due to the valid angle in standard configurations. The proper reorganization of the shifted spectra guaranteed a reliable band over the entire visible domain. Specifically, by combining the multi-view spectra, the redundancy in the overlapping spectral regions was

successfully exploited to average out the background noise, providing a powerful intrinsic denoising effect. Moreover, the analytical conditions and criteria establishing the minimum number of steering directions required to achieve complete spectral recovery were thoroughly discussed. This joint framework led to a significantly enhanced reconstruction accuracy of the array excitations.

Finally, an extensive Monte Carlo numerical analysis demonstrated the effectiveness of the proposed technique, showing a substantially higher probability of detection and strict control over the false alarm rate compared to classical single-view approach.

When scaling the proposed approach to very large arrays, both measurement logistics and computational complexity must be considered, and our method offers distinct advantages in both areas. In standard single-view diagnostics, testing a very large array necessitates an oversized measurement aperture (typically at least $X_0 \geq 2X_s$) to maintain a sufficient valid angle. This translates to a massive number of spatial measurement points M and extremely time-consuming mechanical scanning. A major practical advantage of our multi-view approach is that it fundamentally relaxes this constraint. Because mechanical near-field positioning is inherently slow, whereas changing the state of electronic phase shifters is virtually instantaneous, our method effectively leverages “free” angular diversity from an acquisition-time perspective. Steering diversity successfully compensates for truncation errors even with a highly restricted measurement domain (e.g., $X_0 \approx 1.4X_s$). Therefore, any minimal time spent cycling through L electronic steering views is more than offset by the drastic reduction in the required physical scanning area and the total number of spatial samples M .

The results obtained from the numerical simulations are highly promising. Therefore, necessary future work will focus on validating the strategy with experimental data, extending the proposed diagnostic framework to two-dimensional planar architectures, and considering non-planar geometries such as cylindrical or spherical surfaces.

Author Contributions: Conceptualization, M.A.M. and M.D.P.; data curation, M.D.P.; formal analysis, M.A.M. and M.D.P.; funding acquisition, M.A.M.; investigation, M.A.M. and M.D.P.; methodology, M.A.M. and M.D.P.; project administration, M.A.M. and R.S.; resources, M.A.M. and R.S.; software, M.A.M. and M.D.P.; supervision, M.A.M. and R.S.; validation, M.A.M. and M.D.P.; visualization, M.A.M., M.D.P., R.D., A.C., and A.D.; writing—original draft preparation, M.D.P. and M.A.M.; writing—review and editing, M.D.P., A.D., A.C., R.D., M.D.P., M.A.M., and R.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 104 published on 2 February 2022 by the Italian Ministry of University and Research (MUR), funded by the European Union—NextGenerationEU—Project Title PLasma Advanced Sensing Methodologies And Reconstructions in Ecr ion sources (PLASMARE)—CUP E53D23001060006—Grant Assignment Decree No. 960 adopted on 30 June 2023 by the Italian Ministry of Ministry of University and Research (MUR).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Mailloux, R. *Phased Array Antenna Handbook*, 3rd ed.; Artech: Norwood, MA, USA, 2017.
2. Hasch, J.; Topak, E.; Schnabel, R.; Zwick, T.; Weigel, R.; Waldschmidt, C. Millimeter-Wave Technology for Automotive Radar Sensors in the 77 GHz Frequency Band. *IEEE Trans. Microw. Theory Tech.* **2012**, *60*, 845–860. [CrossRef]
3. Hong, W.; Jiang, Z.H.; Yu, C.; Zhou, J.; Chen, P.; Yu, Z.; Zhang, H.; Yang, B.; Pang, X.; Jiang, M.; et al. Multibeam Antenna Technologies for 5G Wireless Communications. *IEEE Trans. Antennas Propag.* **2017**, *65*, 6231–6249. [CrossRef]

4. Yang, Y.; Mao, M.; Xu, J.; Liu, H.; Wang, J.; Song, K. Millimeter-Wave Antennas for 5G Wireless Communications: Technologies, Challenges, and Future Trends. *Sensors* **2025**, *25*, 5424. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Li, G.; Lu, M. Research Progress on 6G Communication Antenna Technology. *Electronics* **2026**, *15*, 1173. [\[CrossRef\]](#)
6. Boopalan, N.; Ramasamy, A.K.; Nagi, F.; Alkahtani, A.A. Planar Array Failed Element(s) Radiation Pattern Correction: A Comparison. *Appl. Sci.* **2021**, *11*, 9234. [\[CrossRef\]](#)
7. Zou, X.-J.; Wang, Y.-W.; Zong, B.-F.; Xu, X.-G.; Han, L.-X.; Zhu, H.; Song, W.; Tan, M.; Du, H.-N. Miniaturized Low-Profile Ultrawideband Antipodal Vivaldi Antenna Array Loaded with Edge Techniques. *IEEE Trans. Antennas Propag.* **2026**, *74*, 1156–1161. [\[CrossRef\]](#)
8. Wang, C.; Xu, H.-X.; Zhu, R.; Ding, H.; Li, B.; Wang, X.; Yang, C.; Lu, Y. 3-D-Printed Pentahedral Polarization-Division Transmissive Metadevice with Versatile Wavefronts. *IEEE Trans. Antennas Propag.* **2026**, *74*, 4915–4920. [\[CrossRef\]](#)
9. Bucci, O.M.; Migliore, M.D.; Panariello, G.; Sgambato, P. Accurate Diagnosis of Conformal Arrays from Near-Field Data Using the Matrix Method. *IEEE Trans. Antennas Propag.* **2005**, *53*, 1114–1120. [\[CrossRef\]](#)
10. Palmeri, R.; Battaglia, G.M.; Morabito, A.F.; Costanzo, S.; Venneri, F.; Isernia, T. Fault Diagnosis of Realistic Arrays From a Reduced Number of Phaseless Near-Field Measurements. *IEEE Trans. Antennas Propag.* **2023**, *71*, 7206–7219. [\[CrossRef\]](#)
11. Maisto, M.A.; Del Prete, M.; Cuccaro, A.; Solimene, R. Near-Field Phased Array Diagnostics by a Subspace Projection Method. *IEEE Access* **2024**, *12*, 80283–80299. [\[CrossRef\]](#)
12. Boopalan, N.; Ramasamy, A.K.; Nagi, F. A Comparison of Faulty Antenna Detection Methodologies in Planar Array. *Appl. Sci.* **2023**, *13*, 3695. [\[CrossRef\]](#)
13. Buonanno, A.; D'Urso, M.; Cicolani, M.; Mosca, S. Large Phased Arrays Diagnostic via Distributional Approach. *PIER* **2009**, *92*, 153–166. [\[CrossRef\]](#)
14. Bai, G.; Liao, C.; Liu, Y.; Cheng, Y.-F. Rapid Failure Diagnosis of Impaired Linear Antenna Arrays Based on Matrix Pencil Method. *Antennas Wirel. Propag. Lett.* **2022**, *21*, 1708–1712. [\[CrossRef\]](#)
15. Famoriji, O.J.; Shongwe, T. An Effective Antenna Array Diagnosis Method via Multivalued Neural Network Inverse Modeling Approach. *AEM* **2021**, *10*, 58–70. [\[CrossRef\]](#)
16. Yao, H.M.; Li, M.; Jiang, L.; Yeung, K.L.; Ng, M. Antenna Array Diagnosis Using a Deep Learning Approach. *IEEE Trans. Antennas Propag.* **2024**, *72*, 5396–5401. [\[CrossRef\]](#)
17. Gattoufi, L.; Picard, D.; Rahmat Samii, Y.; Bolomey, J.C. Regularized Matrix Method for Near-Field Diagnostic Techniques of Phased Array Antennas. In *Proceedings of the IEEE Antennas and Propagation Society International Symposium, Montreal, QC, Canada 13–18 July 1997*; IEEE: New York, NY, USA, 1997; Volume 2, pp. 1066–1069.
18. Pan, C.; Ba, X.; Tang, Y.; Zhang, F.; Zhang, Y.; Wang, Z.; Fan, W. Phased Array Antenna Calibration Method Experimental Validation and Comparison. *Electronics* **2023**, *12*, 489. [\[CrossRef\]](#)
19. Xiong, C.; Xiao, G. Excitation Retrieval for Phased Arrays with Magnitude-Only Fields Measured at a Fixed Location. *Antennas Wirel. Propag. Lett.* **2021**, *20*, 264–268. [\[CrossRef\]](#)
20. Petre, P.; Sarkar, T.K. Planar Near-Field to Far-Field Transformation Using an Equivalent Magnetic Current Approach. *IEEE Trans. Antennas Propag.* **1992**, *40*, 1348–1356. [\[CrossRef\]](#)
21. Yaghjian, A. An Overview of Near-Field Antenna Measurements. *IEEE Trans. Antennas Propag.* **1986**, *34*, 30–45. [\[CrossRef\]](#)
22. Hansen, T.B.; Yaghjian, A.D. *Plane-Wave Theory of Time-Domain Fields*; IEEE: New York, NY, USA, 1999; ISBN 9780470545522.
23. Leach, W.; Paris, D. Probe compensated near-field measurements on a cylinder. *IRE Trans. Antennas Propag.* **1973**, *21*, 435–445. [\[CrossRef\]](#)
24. Hansen, J.E. *Spherical Near-Field Antenna Measurements*; Peter Peregrinus: London, UK, 1988.
25. Lee, J.J.; Ferren, E.M.; Woollen, D.P.; Lee, K.M. Near-Field Probe Used as a Diagnostic Tool to Locate Defective Elements in an Array Antenna. *IEEE Trans. Antennas Propag.* **1988**, *36*, 884–889. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Maisto, M.A.; Solimene, R.; Pierri, R. Valid Angle Criterion and Radiation Pattern Estimation via Singular Value Decomposition for Planar Scanning. *IET Microwaves Antenna Prop.* **2019**, *13*, 2342–2348. [\[CrossRef\]](#)
27. Foged, L.J.; Scialacqua, L.; Saccardi, F.; Mioc, F.; Quijano, J.L.A.; Martini, E.; Maci, S.; Sabbadini, M.; Vecchi, G. Comparative Investigation of Methods to Reduce Truncation Errors in Partial Spherical Near-Field Antenna Measurements. In *Proceedings of the 2012 6th European Conference on Antennas and Propagation (EUCAP)*, Prague, Czech Republic, 26–30 March 2012; pp. 2533–2537.
28. Kim, K.T. Truncation-Error Reduction in 2D Cylindrical/Spherical Near-Field Scanning. *IEEE Trans. Antennas Propag.* **2010**, *58*, 2153–2158. [\[CrossRef\]](#)
29. Cano-Fácila, F.J.; Pivnenko, S.; Sierra-Castañer, M. Reduction of Truncation Errors in Planar, Cylindrical, and Partial Spherical Near-Field Antenna Measurements. *Int. J. Antennas Propag.* **2012**, *2012*, 438727. [\[CrossRef\]](#)
30. Bucci, O.M.; D'Elia, G.; Migliore, M.D. A New Strategy to Reduce the Truncation Error in Near-Field/Far-Field Transformations. *Radio Sci.* **2000**, *35*, 3–17. [\[CrossRef\]](#)

31. Bolomey, J.-C.; Bucci, O.M.; Casavola, L.; D’Elia, G.; Migliore, M.D.; Ziyat, A. Reduction of Truncation Error in Near-Field Measurements of Antennas of Base-Station Mobile Communication Systems. *IEEE Trans. Antennas Propagat.* **2004**, *52*, 593–602. [\[CrossRef\]](#)
32. Martini, E.; Breinbjerg, O.; Maci, S. Reduction of Truncation Errors in Planar Near-Field Aperture Antenna Measurements Using the Gerchberg-Papoulis Algorithm. *IEEE Trans. Antennas Propag.* **2008**, *56*, 3485–3493. [\[CrossRef\]](#)
33. Del Prete, M.; Leone, G. Planar Phased Array Antenna Diagnostics by a MUSIC-Based Algorithm. In Proceedings of the 2022 IEEE Conference on Antenna Measurements and Applications (CAMA), Guangzhou, China, 14–17 December 2022; pp. 1–3.
34. Del Prete, M.; Maisto, M.A.; Leone, G. Data Reduction in Linear Phased Array Diagnostic by a TR-MUSIC Based Approach. In Proceedings of the 2023 17th European Conference on Antennas and Propagation (EuCAP), Florence, Italy, 26–31 March 2023; pp. 1–4.
35. Xiong, C.; Xiao, G.; Hou, Y.; Hameed, M. A Compressed Sensing-Based Element Failure Diagnosis Method for Phased Array Antenna During Beam Steering. *IEEE Antennas Wirel. Propag. Lett.* **2019**, *18*, 1756–1760. [\[CrossRef\]](#)
36. Del Prete, M.; Cuccaro, A.; Solimene, R.; Maisto, M.A. Near-Field Phased Array Diagnostics in Steering Domain. *IEEE Antennas Wirel. Propag. Lett.* **2025**, *24*, 4860–4864. [\[CrossRef\]](#)
37. Levanon, N. *Radar Principle*; Wiley: New York, NY, USA, 1988.
38. Solimene, R.; Maisto, M.A.; Pierri, R. Role of Diversity on the Singular Values of Linear Scattering Operators: The Case of Strip Objects. *J. Opt. Soc. Am. A JOSAA* **2013**, *30*, 2266–2272. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Maisto, M.A.; Del Prete, M.; Leone, G.; Pierri, R.; Solimene, R. Non-Uniform Warping Sampling for Data Reduction in Planar Array Diagnostics. *IEEE Access* **2022**, *10*, 82336–82345. [\[CrossRef\]](#)
40. Migliore, M.D. Array Diagnosis From Far-Field Data Using the Theory of Random Partial Fourier Matrices. *Antennas Wirel. Propag. Lett.* **2013**, *12*, 745–748. [\[CrossRef\]](#)
41. Migliore, M.D. A Compressed Sensing Approach for Array Diagnosis From a Small Set of Near-Field Measurements. *IEEE Trans. Antennas Propagat.* **2011**, *59*, 2127–2133. [\[CrossRef\]](#)
42. Lin, Z.; Chen, Y.; Liu, X.; Jiang, R.; Shen, B. A Bayesian Compressive Sensing-Based Planar Array Diagnosis Approach From Near-Field Measurements. *Antennas Wirel. Propag. Lett.* **2021**, *20*, 249–253. [\[CrossRef\]](#)
43. Schenone, V.; Fedeli, A.; Randazzo, A. An Antenna Array Diagnosis Approach Based on CNN Inversion and CFAR Detection. *IEEE Trans. Antennas Propagat.* **2025**, *73*, 6252–6262. [\[CrossRef\]](#)
44. Salucci, M.; Gelmini, A.; Oliveri, G.; Massa, A. Planar Array Diagnosis by Means of an Advanced Bayesian Compressive Processing. *IEEE Trans. Antennas Propagat.* **2018**, *66*, 5892–5906. [\[CrossRef\]](#)
45. Schenone, V.; Fedeli, A.; Estatico, C.; Pastorino, M.; Randazzo, A. Detection of Failures in Antenna Arrays Through a Lebesgue-Space Approach. *IEEE Open J. Antennas Propag.* **2022**, *3*, 652–662. [\[CrossRef\]](#)
46. Morabito, A.F.; Palmeri, R.; Isernia, T. A Compressive-Sensing-Inspired Procedure for Array Antenna Diagnostics by a Small Number of Phaseless Measurements. *IEEE Trans. Antennas Propagat.* **2016**, *64*, 3260–3265. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.