

HALF INVERTED NESTED ARRAYS WITH LARGE HOLE-FREE FOURTH-ORDER DIFFERENCE CO-ARRAYS

Yuan-Pon Chen¹ and Chun-Lin Liu²

Dept. of Electrical Engineering², Graduate Institute of Communication Engineering^{1,2}
National Taiwan University, Taipei, Taiwan 10617
r10942064@ntu.edu.tw¹ and chunlinliu@ntu.edu.tw²

ABSTRACT

Sparse arrays with fourth-order cumulant processing can identify up to $\mathcal{O}(N^4)$ source directions with only N physical sensors. To achieve this property, the fourth-order difference co-array is preferable to own a contiguous segment with no holes. However, existing sparse array designs either have holes in the co-array of size $\mathcal{O}(N^4)$ or own fewer than $\mathcal{O}(N^4)$ elements in the hole-free co-array. This paper proposes the half inverted nested array (HINA), which consists of a nested array and an inverted, scaled, and shifted nested array. By maximizing the size of the co-array, it can be shown that HINA with the optimal parameters possesses a hole-free fourth-order difference co-array of size $\mathcal{O}(N^4)$. Numerical examples demonstrate the improved DOA estimation performance of HINA.

Index Terms— Sparse arrays, fourth-order difference co-arrays, nested array, direction of arrival estimation.

1. INTRODUCTION

In array processing, estimating the direction-of-arrivals (DOAs) of the incoming source signals is widely studied [1, 2] and has been developed for decades. It is known that both the source statistics and the array configuration play a significant role in the estimation performance [3–5]. In particular, fourth-order cumulant data processing on sparse arrays is capable of resolving $\mathcal{O}(N^4)$ source DOAs with N physical sensors and statistically independent non-Gaussian source signals [6]. In contrast, the uniform linear array (ULA) only finds $\mathcal{O}(N)$ DOAs with the same number of sensors [7, 8]. The reason is that the fourth-order difference co-array, denoted by \mathbb{D}_4 , has size $\mathcal{O}(N^4)$ for sparse arrays, but \mathbb{D}_4 is only $\mathcal{O}(N)$ for the ULA.

The structure of \mathbb{D}_4 is also critical to the applicability of DOA estimators. It is ubiquitous to deploy the variants of the multiple signal classification (MUSIC) algorithm on the cumulant information defined on \mathbb{D}_4 [6, 9–13]. This co-array-based MUSIC algorithm attains the resolvability of $\mathcal{O}(N^4)$ DOAs for sparse arrays if the fourth-order difference co-array \mathbb{D}_4 contains a large central ULA segment \mathbb{U}_4 of size $\mathcal{O}(N^4)$. However, the co-array-based MUSIC algorithm [6] only takes the cumulant information on \mathbb{U}_4 and discards the information beyond \mathbb{U}_4 . As a result, it is desirable to have a *hole-free* fourth-order difference co-array (i.e. $\mathbb{D}_4 = \mathbb{U}_4$) to fully exploit the information on \mathbb{D}_4 [13]. Furthermore, hole-free \mathbb{D}_4 results in a smaller aperture in the physical array, making it useful in scenarios where the physical aperture is fixed [14].

From this viewpoint, array configurations satisfying both $|\mathbb{U}_4| = \mathcal{O}(N^4)$ and $\mathbb{D}_4 = \mathbb{U}_4$ have been of considerable interest. In the literature, these properties on \mathbb{D}_4 were addressed by two families of sparse arrays. The first family of sparse arrays owns a *central ULA segment* \mathbb{U}_4 of size $\mathcal{O}(N^4)$, but there are holes in their \mathbb{D}_4 . These arrays include the fourth-level nested array (FL-NA) [6], the sparse array extension with the fourth-order difference co-array enhancement based on the two-level nested array (SAFOE-NA) [15], the expanding and shift scheme with two nested arrays (EAS-NA-NA) [16] and that with large spacing (EAS-NA-NA_{LS}) [9], and the enhanced four-level nested array (E-FL-NA) [10]. Among these arrays, the EAS-NA-NA_{LS} achieves the largest \mathbb{U}_4 for sufficiently large N , but its \mathbb{D}_4 contains holes.

The second family of array geometries aims for *large hole-free* \mathbb{D}_4 . This family contains the compressed nested array (CNA) [11], the two-level nested array for fourth-order-cumulant-based DOA (2L-FO-NA) [12], and the extended Cantor array based on fourth-order difference co-arrays (E-FO-Cantor) [13]. However, for these arrays, the size of \mathbb{U}_4 is compromised for the hole-free property $\mathbb{D}_4 = \mathbb{U}_4$. More specifically, for sufficiently large N , the size of \mathbb{U}_4 is $\mathcal{O}(N^2)$ for the CNA [11], $\mathcal{O}(N^2)$ for the 2L-FO-NA [12], and $\mathcal{O}(N^{3.17})$ for the E-FO-Cantor [13]. None of them achieves $|\mathbb{U}_4| = \mathcal{O}(N^4)$. Presented with these two families of array designs, sparse arrays satisfying $|\mathbb{D}_4| = |\mathbb{U}_4| = \mathcal{O}(N^4)$ remain open.

In this paper, we propose the half inverted nested array (HINA) to meet the property that $|\mathbb{D}_4| = |\mathbb{U}_4| = \mathcal{O}(N^4)$. HINA is composed of two nested arrays. The first half of HINA is a nested array aligned to the origin, while the second half of HINA is an inverted, scaled, and shifted nested array. With closed-form expressions of the parameters, HINA achieves a hole-free \mathbb{D}_4 for $N \geq 4$ sensors. Based on this result, we maximize the size of \mathbb{U}_4 of HINA with N sensors. According to the explicit expressions of the optimal parameters, $|\mathbb{U}_4|$ of HINA has an asymptotic expression of $N^4/64 = \mathcal{O}(N^4)$ for sufficiently large N . Note that the $|\mathbb{U}_4|$ of HINA is larger than that of the existing arrays with hole-free \mathbb{D}_4 [11–13]. The $|\mathbb{U}_4|$ of HINA is also comparable to that of the E-FL-NA, whose \mathbb{D}_4 has holes.

Paper outline: Section 2 first reviews DOA estimation with the fourth-order difference co-array, and then reviews the two-level nested array [17]. Section 3 defines HINA, proves the hole-free property of its \mathbb{D}_4 , and derives the parameters that maximize $|\mathbb{U}_4|$. Section 4 compares several arrays in terms of the size of \mathbb{U}_4 and the DOA estimation performance. Section 5 concludes this paper.

2. PRELIMINARIES

Consider a linear array of N sensors. The sensors are located at $\ell_0\lambda/2, \ell_1\lambda/2, \dots, \ell_{N-1}\lambda/2$, where $\ell_0, \ell_1, \dots, \ell_{N-1}$ are integers

This work was supported in part by the Ministry of Science and Technology, Taiwan, under grant MOST 110-2222-E-002-007- and in part by the Ministry of Education, Taiwan, under the Yushan Young Scholar Program NTU-110V0902.

and λ is the wavelength of the incoming sources. The sensor locations are characterized by an integer set $\mathbb{S} = \{\ell_0, \ell_1, \dots, \ell_{N-1}\}$.

Assume that there are D narrow-band sources impinging on \mathbb{S} from angles $\theta_1, \theta_2, \dots, \theta_D$. The received signal on the sensor at the location $\ell_m \lambda/2$ can be expressed as

$$x_m(t) = \sum_{d=1}^D e^{-j2\pi\ell_m\bar{\theta}_d} s_d(t) + n_m(t), \quad (1)$$

where $s_d(t)$ is the d th source signal, $\bar{\theta}_d = \frac{1}{2} \sin(\theta_d)$ is the normalized DOA as defined in [18], $n_m(t)$ is a zero-mean stationary Gaussian noise, and $m \in \llbracket 0, N-1 \rrbracket$. Here the notation $\llbracket a, b \rrbracket := \{a, a+1, \dots, b\}$ for $a, b \in \mathbb{Z}$ with $a \leq b$. The source signals are assumed to be zero-mean, stationary, non-Gaussian, and statistically independent. The noise term is statistically independent of the sources. Next, we analyze the fourth-order circular cumulant of the received signals associated with the indices $n_1, n_2, n_3, n_4 \in \llbracket 0, N-1 \rrbracket$. The fourth-order circular cumulant of $x_{n_1}(t), x_{n_2}(t), x_{n_3}(t)$, and $x_{n_4}(t)$ is defined as [8, 19]

$$\begin{aligned} \text{Cum}(x_{n_1}(t), x_{n_2}(t), x_{n_3}^*(t), x_{n_4}^*(t)) \\ &:= \mathbb{E}[x_{n_1}(t)x_{n_2}(t)x_{n_3}^*(t)x_{n_4}^*(t)] \\ &\quad - \mathbb{E}[x_{n_1}(t)x_{n_2}(t)]\mathbb{E}[x_{n_3}^*(t)x_{n_4}^*(t)] \\ &\quad - \mathbb{E}[x_{n_1}(t)x_{n_3}^*(t)]\mathbb{E}[x_{n_2}(t)x_{n_4}^*(t)] \\ &\quad - \mathbb{E}[x_{n_1}(t)x_{n_4}^*(t)]\mathbb{E}[x_{n_2}(t)x_{n_3}^*(t)]. \end{aligned} \quad (2)$$

By (1), [6, Theorem 1], and the independence of the source signals and the noise term, the fourth-order cumulant in (2) becomes

$$\begin{aligned} \text{Cum}(x_{n_1}(t), x_{n_2}(t), x_{n_3}^*(t), x_{n_4}^*(t)) \\ &= \sum_{d=1}^D e^{-j2\pi(\ell_{n_1} + \ell_{n_2} - \ell_{n_3} - \ell_{n_4})\bar{\theta}_d} c_d, \end{aligned} \quad (3)$$

where $c_d = \text{Cum}\{s_d(t), s_d(t), s_d^*(t), s_d^*(t)\}$. Note that the relation in (3) resembles the array model in (1). The quantity $\ell_{n_1} + \ell_{n_2} - \ell_{n_3} - \ell_{n_4}$ in (3) can be viewed as the locations on the virtual co-array. For this reason, we define the fourth-order difference co-array as follows [6].

Definition 1. For a linear array $\mathbb{S} = \{\ell_0, \ell_1, \dots, \ell_{N-1}\}$, its fourth-order difference co-array \mathbb{D}_4 is defined as

$$\mathbb{D}_4 := \{\ell_{n_1} + \ell_{n_2} - \ell_{n_3} - \ell_{n_4} \mid n_1, n_2, n_3, n_4 \in \llbracket 0, N-1 \rrbracket\}.$$

By defining the notations $\alpha\mathbb{A} \pm \beta\mathbb{B} := \{\alpha a \pm \beta b \mid a \in \mathbb{A}, b \in \mathbb{B}\}$ for $\mathbb{A}, \mathbb{B} \subseteq \mathbb{R}$ and $\alpha, \beta \in \mathbb{R}$, \mathbb{D}_4 can also be expressed as $\mathbb{D}_4 = \mathbb{S} + \mathbb{S} - \mathbb{S} - \mathbb{S}$. We write $\alpha \pm \beta\mathbb{B} := \{\alpha\} \pm \beta\mathbb{B}$ for later use.

Based on \mathbb{D}_4 , the central ULA segment \mathbb{U}_4 is defined to be the longest unit-spacing ULA in \mathbb{D}_4 with the element 0 included. More specifically, $\mathbb{U}_4 := \llbracket -U_4, U_4 \rrbracket$ where $U_4 := \max\{m \in \mathbb{Z} \mid \llbracket -m, m \rrbracket \subseteq \mathbb{D}_4\}$. For more insight into the structure of \mathbb{D}_4 , two other kinds of co-arrays are also defined here: the second-order difference co-array of \mathbb{S} is defined as $\mathbb{D}_2 := \mathbb{S} - \mathbb{S}$, and the sum co-array of \mathbb{S} is defined as $\mathbb{S}_2 := \mathbb{S} + \mathbb{S}$. By Definition 1, we obtain the relations that $\mathbb{D}_4 = \mathbb{D}_2 + \mathbb{D}_2 = \mathbb{S}_2 - \mathbb{S}_2$.

Next, we review the (two-level) nested array [17], which is a fundamental building block of HINA. A nested array with two parameters N_1 and N_2 is composed of a dense ULA with N_1 sensors and a sparse ULA with N_2 sensors. The parameters N_1 and N_2 are positive integers. With the left-most sensor aligned to the origin, \mathbb{S}_{NA} is defined as

$$\mathbb{S}_{\text{NA}} := \llbracket 0, N_1 - 1 \rrbracket \cup \{(N_1 + 1)n - 1 \mid n \in \llbracket 1, N_2 \rrbracket\}. \quad (4)$$

Furthermore, the nested array possesses a large ULA segment in both its difference co-array $\mathbb{D}_{2,\text{NA}}$ and sum co-array $\mathbb{S}_{2,\text{NA}}$. These segments satisfy [17, 20]

$$\mathbb{D}_{2,\text{NA}} = \mathbb{S}_{\text{NA}} - \mathbb{S}_{\text{NA}} = \llbracket -(N_1 + 1)N_2 + 1, (N_1 + 1)N_2 - 1 \rrbracket, \quad (5)$$

$$\mathbb{S}_{2,\text{NA}} = \mathbb{S}_{\text{NA}} + \mathbb{S}_{\text{NA}} \supseteq \llbracket 0, (N_1 + 1)(N_2 + 1) - 2 \rrbracket. \quad (6)$$

3. HALF INVERTED NESTED ARRAY

3.1. Half Inverted Nested Array

Definition 2. Let $\mathbb{S}_{\text{NA}}^{(1)}$ be a nested array with parameters N_1 and N_2 and let $\mathbb{S}_{\text{NA}}^{(2)}$ be a nested array with parameters N_3 and N_4 . Define $\mathbb{S}_1 := \sigma(L - \mathbb{S}_{\text{NA}}^{(2)})$ to be the inverted array derived from $\mathbb{S}_{\text{NA}}^{(2)}$, where $\sigma := (N_1 + 1)(N_2 + 1) - 1$ and $L := (N_3 + 1)(N_4 + 1)$. The *half inverted nested array* (HINA) \mathbb{S}_{HI} is defined as

$$\mathbb{S}_{\text{HI}} := \mathbb{S}_{\text{NA}}^{(1)} \cup \mathbb{S}_1.$$

HINA consists of two nested arrays, and the second one is adjusted. This design rule can also be seen in the EAS-NA-NA [16] and the G-FODC_{NA} [21]. The second nested array of all three designs is scaled up by a factor, and that of HINA and the EAS-NA-NA is shifted. However, the second nested array of HINA (which takes up about *half* of HINA's sensors) is first *inverted* in the sense of having a negative sign in front of it. Besides, both the scaling factor and the shift offset of HINA are different from those of the EAS-NA-NA and the G-FODC_{NA}.

HINA can also be seen as the union of four ULAs with different spacing. This structure is similar to that of the four-level *nested array* (FL-NA) [6] and the E-FL-NA [10]. The FL-NA and the E-FL-NA have increasing spacing from the leftmost ULA to the rightmost one, while HINA has its third ULA with the largest spacing.

HINA has a total number of sensors $N = N_1 + N_2 + N_3 + N_4$, where $N_1 + N_2$ sensors are from $\mathbb{S}_{\text{NA}}^{(1)}$ and $N_3 + N_4$ sensors are from \mathbb{S}_1 . Since N_1, N_2, N_3 , and N_4 are all positive integers, HINA is only defined for $N \geq 4$.

Theorem 1. HINA has a hole-free fourth-order difference co-array $\mathbb{D}_{4,\text{HI}} = \llbracket -2L\sigma, 2L\sigma \rrbracket$.

Proof sketch. We first show that $\mathbb{D}_{4,\text{HI}} \subseteq \llbracket -2L\sigma, 2L\sigma \rrbracket$. This can be seen by that $\max(\mathbb{S}_{\text{HI}}) - \min(\mathbb{S}_{\text{HI}}) = L\sigma$, and hence the largest element and the smallest element of $\mathbb{D}_{4,\text{HI}}$ are $2L\sigma$ and $-2L\sigma$, respectively.

Next, we show that $\mathbb{D}_{4,\text{HI}} \supseteq \llbracket -2L\sigma, 2L\sigma \rrbracket$. Since any \mathbb{D}_4 is symmetric about 0, it suffices to show that $\mathbb{D}_{4,\text{HI}} \supseteq \llbracket 0, 2L\sigma \rrbracket$. The interval $\llbracket 0, 2L\sigma \rrbracket$ is divided into six disjoint sub-intervals:

$$\mathbb{I}_1 := \llbracket 0, (L - N_3 - 1)\sigma - N_1 - 1 \rrbracket, \quad (7)$$

$$\mathbb{I}_2 := \llbracket (L - N_3 - 1)\sigma - N_1, (L - N_3 - 1)\sigma \rrbracket, \quad (8)$$

$$\mathbb{I}_3 := \llbracket (L - N_3 - 1)\sigma + 1, L\sigma \rrbracket, \quad (9)$$

$$\mathbb{I}_4 := \llbracket L\sigma + 1, (L + 1)\sigma - N_1 - 1 \rrbracket, \quad (10)$$

$$\mathbb{I}_5 := \llbracket (L + 1)\sigma - N_1, (L + 1)\sigma \rrbracket, \quad (11)$$

$$\mathbb{I}_6 := \llbracket (L + 1)\sigma + 1, 2L\sigma \rrbracket. \quad (12)$$

To analyze $\mathbb{D}_{4,\text{HI}}$, we first consider the following difference co-arrays

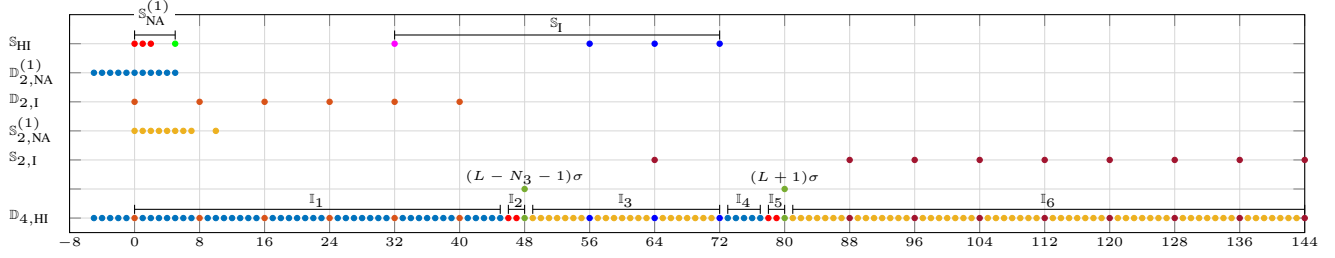


Fig. 1: An illustration of HINA \mathbb{S}_{HI} with $N_1 = N_2 = N_3 = N_4 = 2$ and the structure of the fourth-order difference co-array \mathbb{D}_{HI} .

and sum co-arrays, according to (5), (6), and Definition 2,

$$\mathbb{D}_{2,\text{NA}}^{(1)} := \mathbb{S}_{\text{NA}}^{(1)} - \mathbb{S}_{\text{NA}}^{(1)} = \llbracket -\sigma + N_1 + 1, \sigma - N_1 - 1 \rrbracket, \quad (13)$$

$$\mathbb{S}_{2,\text{NA}}^{(1)} := \mathbb{S}_{\text{NA}}^{(1)} + \mathbb{S}_{\text{NA}}^{(1)} \supseteq \llbracket 0, \sigma - 1 \rrbracket, \quad (14)$$

$$\mathbb{D}_{2,\text{NA}}^{(2)} := \mathbb{S}_{\text{NA}}^{(2)} - \mathbb{S}_{\text{NA}}^{(2)} = \llbracket -L + N_3 + 2, L - N_3 - 2 \rrbracket, \quad (15)$$

$$\mathbb{S}_{2,\text{NA}}^{(2)} := \mathbb{S}_{\text{NA}}^{(2)} + \mathbb{S}_{\text{NA}}^{(2)} \supseteq \llbracket 0, L - 2 \rrbracket. \quad (16)$$

By (15) and (16), the co-arrays of \mathbb{S}_I satisfy

$$\mathbb{D}_{2,I} := \mathbb{S}_I - \mathbb{S}_I = \sigma \llbracket -L + N_3 + 2, L - N_3 - 2 \rrbracket, \quad (17)$$

$$\mathbb{S}_{2,I} := \mathbb{S}_I + \mathbb{S}_I \supseteq 2L\sigma - \sigma \llbracket 0, L - 2 \rrbracket. \quad (18)$$

We also define the following sets

$$\mathbb{K}_1 := \mathbb{D}_{2,I} + \mathbb{D}_{2,\text{NA}}^{(1)}, \quad \mathbb{K}_2 := (L - N_3 - 1)\sigma - \mathbb{S}_{\text{NA,dense}}^{(1)},$$

$$\mathbb{K}_3 := \mathbb{S}_{\text{I,dense}} - \mathbb{S}_{2,\text{NA}}^{(1)}, \quad \mathbb{K}_4 := L\sigma + \mathbb{D}_{2,\text{NA}}^{(1)},$$

$$\mathbb{K}_5 := (L + 1)\sigma - \mathbb{S}_{\text{NA,dense}}^{(1)}, \quad \mathbb{K}_6 := \mathbb{S}_{2,I} - \mathbb{S}_{2,\text{NA}}^{(1)},$$

where $\mathbb{S}_{\text{NA,dense}}^{(1)} := \llbracket 0, N_1 \rrbracket$ and $\mathbb{S}_{\text{I,dense}} := \sigma(L - \llbracket 0, N_3 \rrbracket)$ denote the dense ULA part of $\mathbb{S}_{\text{NA}}^{(1)}$ and \mathbb{S}_I , respectively.

With these notations, it can be shown that $\mathbb{K}_k \subseteq \mathbb{D}_{4,\text{HI}}$ for $k \in \llbracket 1, 6 \rrbracket$, according to Definition 1 and the fact that $0, (L - N_3)\sigma, (L - 1)\sigma, L\sigma \in \mathbb{S}_{\text{HI}}$. Besides, by (13), (17) and the fact that $2(\sigma - N_1 - 1) + 1 \geq \sigma$, we obtain $\mathbb{K}_1 \supseteq \mathbb{I}_1$. By (13), (14), (18), it can be shown that $\mathbb{K}_k \supseteq \mathbb{I}_k$ for $k \in \llbracket 2, 6 \rrbracket$. Altogether, $\mathbb{D}_{4,\text{HI}} \supseteq \bigcup_{k=1}^6 \mathbb{K}_k \supseteq \bigcup_{k=1}^6 \mathbb{I}_k = \llbracket 0, 2L\sigma \rrbracket$. These arguments complete the proof. \square

Fig. 1 illustrates the proof of Theorem 1 with $N_1 = N_2 = N_3 = N_4 = 2$ and $\mathbb{S}_{\text{HI}} = \{0, 1, 2, 5, 32, 56, 64, 72\}$. Each row in Fig. 1 illustrates the elements of the sets associated with the proof of Theorem 1. The four sub-arrays of \mathbb{S}_{HI} are colored differently in Fig. 1. According to the $\mathbb{S}_{2,\text{NA}}^{(1)}$ and $\mathbb{S}_{2,I}$ in Fig. 1, $\mathbb{K}_6 = \{54\} \cup \llbracket 57, 64 \rrbracket \cup \{78\} \cup \llbracket 81, 144 \rrbracket$, which is a superset of $\mathbb{I}_6 = \llbracket 81, 144 \rrbracket$.

The design of HINA utilizes the \mathbb{D}_2 , the \mathbb{S}_2 , and even the original structure of the two-level nested array. The coverage of \mathbb{I}_1 makes use of both $\mathbb{D}_{2,\text{NA}}^{(1)}$ and $\mathbb{D}_{2,I}$. This is based on the fact that $\mathbb{D}_4 = \mathbb{D}_2 + \mathbb{D}_2$, which is inspired by the G-FODC [21] and the EAS scheme [16]. On the other hand, covering \mathbb{I}_6 takes both $\mathbb{S}_{2,\text{NA}}^{(1)}$ and $\mathbb{S}_{2,I}$. This is based on the fact that $\mathbb{D}_4 = \mathbb{S}_2 - \mathbb{S}_2$, which only the EAS-NA- NA_{LS} takes into consideration [9]. Besides, the dense ULA parts of \mathbb{S}_I and $\mathbb{S}_{\text{NA}}^{(1)}$ also play an important role in covering \mathbb{I}_2 , \mathbb{I}_3 , and \mathbb{I}_5 .

3.2. Co-array Maximization of HINA

When the number of sensors N is fixed, it is preferable to maximize the central ULA segment of the co-array. Thus, we cast the following

optimization problem for the parameters N_1, N_2, N_3 , and N_4 :

$$\max_{N_1, N_2, N_3, N_4 \in \mathbb{N}} U_{\text{HI}}(N_1, N_2, N_3, N_4) \quad (19a)$$

$$\text{subject to} \quad N_1 + N_2 + N_3 + N_4 = N, \quad (19b)$$

where $U_{\text{HI}}(N_1, N_2, N_3, N_4) := 2L\sigma$ denotes the U_4 of HINA.

Theorem 2. One of the optimal solutions to (19) is

$$(\mathcal{N}_1^{\text{opt}}, \mathcal{N}_2^{\text{opt}}, \mathcal{N}_3^{\text{opt}}, \mathcal{N}_4^{\text{opt}}) = \begin{cases} (k, k, k, k), & \text{if } N = 4k, \\ (k + 1, k, k, k), & \text{if } N = 4k + 1, \\ (k + 1, k + 1, k, k), & \text{if } N = 4k + 2, \\ (k + 1, k + 1, k + 1, k), & \text{if } N = 4k + 3. \end{cases} \quad (20)$$

Proof sketch. This proof is inspired by the proof of [6, Theorem 3]. We first give the maximum difference between any two parameters, and then show that these parameters are roughly equally divided.

First, note that the parameters N_1 and N_2 in U_{HI} are interchangeable, and so are the parameters N_3 and N_4 in U_{HI} . More specifically,

$$U_{\text{HI}}(N_1, N_2, N_3, N_4) = U_{\text{HI}}(N_2, N_1, N_3, N_4) \quad (21)$$

$$= U_{\text{HI}}(N_1, N_2, N_4, N_3). \quad (22)$$

Next, we claim that the optimal solutions to (19) cannot have any two N_i and N_j differing by more than 1. Due to the interchangeability between N_1 and N_2 in (21) and that between N_3 and N_4 in (22), it suffices to consider four cases only. We denote $\mathbb{S}_{\text{HI}}(N_1, N_2, N_3, N_4)$ as HINA with the parameters N_1, N_2, N_3 , and N_4 in what follows.

Case 1 is associated with the condition that $N_1 - N_3 \geq 2$. In Case 1, it can be shown that $\mathbb{S}_{\text{HI}}(N_1 - 1, N_2, N_3 + 1, N_4)$ and $\mathbb{S}_{\text{HI}}(N_1, N_2, N_3, N_4)$ share the same number of sensors. Furthermore, it can be shown that $U_{\text{HI}}(N_1 - 1, N_2, N_3 + 1, N_4)$ is greater than $U_{\text{HI}}(N_1, N_2, N_3, N_4)$. Namely, we can sequentially reduce $N_3 - N_1$ to increase the objective function in (19a) and to maintain the constraint in (19b) simultaneously. Therefore, the optimal solutions to (19) do not satisfy $N_1 - N_3 \geq 2$.

Case 2 considers the condition that $N_3 - N_1 \geq 2$. Similar to the argument in Case 1, it can be shown that $U_{\text{HI}}(N_1 + 1, N_2, N_3 - 1, N_4)$ is greater than $U_{\text{HI}}(N_1, N_2, N_3, N_4)$. Therefore, the optimal solutions to (19) do not meet the condition that $N_3 - N_1 \geq 2$. The same proof technique applies to *Case 3* ($N_1 - N_2 \geq 2$) and *Case 4* ($N_3 - N_4 \geq 2$).

In addition to Cases 1 to 4, the optimal solutions satisfy the condition that $N_2 \geq N_3$. This condition arises from the following argument. If $N_2 < N_3$, then it can be shown that $U_{\text{HI}}(N_1, N_3, N_2, N_4)$ is greater than $U_{\text{HI}}(N_1, N_2, N_3, N_4)$.

Next, with the constraints on the optimal solutions to (19), we let $(\mathcal{N}_1^{\text{opt}}, \mathcal{N}_2^{\text{opt}}, \mathcal{N}_3^{\text{opt}}, \mathcal{N}_4^{\text{opt}})$ be an optimal solution to (19). By (21)

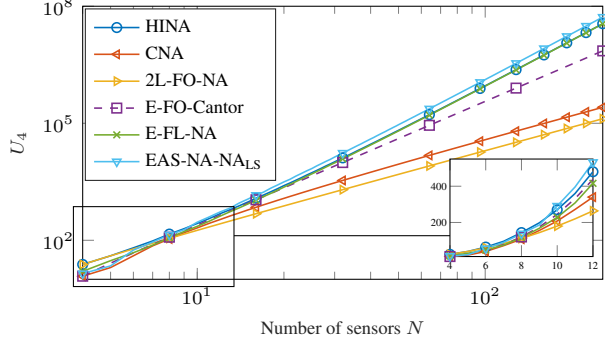


Fig. 2: The dependence of the parameter U_4 on the number of sensors for $N \in [4, 256]$. For arrays other than the E-FO-Cantor, the solid curves are plotted over all $N \in [4, 256]$. For the E-FO-Cantor, the dashed curve represented the theoretical relation $U_4 = N^2 \log_2 3 / 6 - 1.5$.

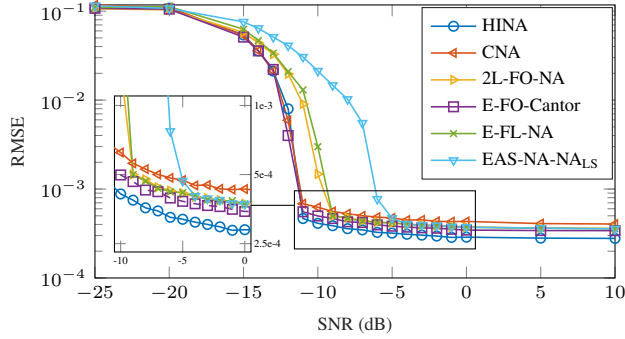


Fig. 3: The RMSE over SNR for the arrays in Table 1. There are $D = 13$ equal-powered sources with normalized DOAs $\bar{\theta}_d$ evenly distributed in $[-0.49, 0.49]$. The number of snapshots is 10^4 . Each data point results from $R = 500$ Monte-Carlo trials.

and (22) we can assume without loss of generality $N_1^{\text{opt}} \geq N_2^{\text{opt}}$ and $N_3^{\text{opt}} \geq N_4^{\text{opt}}$. By the properties that no N_i and N_j can differ by more than 1 and that $N_2^{\text{opt}} \geq N_3^{\text{opt}}$, we write $N_i^{\text{opt}} = \bar{N} + \varepsilon_i$ for $i \in [1, 3]$, and $N_4^{\text{opt}} = \bar{N}$, where \bar{N} is some integer and $\varepsilon_1, \varepsilon_2, \varepsilon_3 \in \{0, 1\}$ with $\varepsilon_1 \geq \varepsilon_2 \geq \varepsilon_3$. By (19b), $4\bar{N} + (\varepsilon_1 + \varepsilon_2 + \varepsilon_3) = N = 4k + l$, where k and l are the quotient and the remainder of N divided by 4, respectively. Finally, by the uniqueness of the remainder and the fact that $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 \in [0, 3]$, $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 = l$ and $\bar{N} = k$. The solution given in (20) is derived by discussing different values of l and taking into consideration the fact that $\varepsilon_1 \geq \varepsilon_2 \geq \varepsilon_3$. \square

As a remark, for sufficiently large N , the parameter U_4 of HINA has an asymptotic expression $U_{4,\text{HI}} \approx N^4 / 128$. This expression is a direct consequence of Theorem 2 and (19a).

4. NUMERICAL EXAMPLES

In this section, we compare several arrays, including HINA, CNA [11], 2L-FO-NA [12], E-FO-Cantor [13], E-FL-NA [10], and EAS-NA-NA_{LS} [9], with respect to their U_4 and DOA estimation performance. Among these arrays, HINA, CNA, 2L-FO-NA, and E-FO-Cantor have hole-free \mathbb{D}_4 . E-FL-NA and EAS-NA-NA_{LS} have holes in their \mathbb{D}_4 .

Table 1: Parameters for array configurations ($N = 8$)

Array	Parameters*	Sensors	U_4	Hole-free \mathbb{D}_4
HINA (Prop.)	(2,2,2,2)	{0,1,2,5,32,56,64,72}	144	Yes
CNA [11]	(4,6)	{0,1,3,4,9,27,45,54}	108	Yes
2L-FO-NA [12]	(4,4)	{0,1,2,3,35,42,49,56}	112	Yes
E-FO-Cantor [13]	2	{0,1,3,4,24,33,51,60}	120	Yes
E-FL-NA [10]	(3,3,2,3)	{1,2,3,6,9,26,68,110}	117	No
EAS-NA-NA _{LS} [9]	(2,3,2,2)	{0,1,2,5,8,33,58,133}	141	No

*Parameters are either (N_1, \dots, N_m) , $m \in [2, 4]$ or r .

Fig. 2 compares the U_4 versus the number of sensors N . In Fig. 2 in the log-log scale, the slope of the curve of HINA is the same as those of the E-FL-NA and the EAS-NA-NA_{LS} and is steeper than the others. This phenomenon validates that HINA, the E-FL-NA and the EAS-NA-NA_{LS} possess $U_4 = \mathcal{O}(N^4)$. Among these arrays in Fig. 2, HINA is the only array with a hole-free \mathbb{D}_4 and $U_4 = \mathcal{O}(N^4)$ at the same time. In the zoom-in plot in Fig. 2, HINA owns the largest U_4 for $N \in [4, 9]$ and the second largest U_4 for $N \in [10, 12]$.

In Fig. 3, we compare the DOA estimation performance among the array configurations in Table 1. All these arrays have $N = 8$ sensors. There are $D = 13$ equal-powered sources, whose normalized DOAs $\bar{\theta}_d$ for $d \in [1, D]$ are evenly distributed from -0.49 to 0.49 . The source signals $s_d(t)$ for $d \in [1, D]$ are 16-QAM symbol sequences modulated from D statistically independent random bit sequences. We apply the co-array MUSIC algorithm [22] on the Hermitian Toeplitz matrix associated with the fourth-order difference co-array. The number of snapshots is 10^4 . The SNR is defined to be E_b/N_0 , where $E_b := \mathbb{E}[|s_1(t)|^2] / \log_2 M$ with $M = 16$ being the number of different symbols, and $N_0 := \mathbb{E}[|n_1(t)|^2]$. The simulation is performed with $R = 500$ Monte-Carlo trials. The MSE at the r th trial is defined by $\text{MSE}^{(r)} := \frac{1}{D} \sum_{d=1}^D (\bar{\theta}_d - \hat{\bar{\theta}}_d^{(r)})^2$, where $\hat{\bar{\theta}}_d^{(r)}$ is the d th estimated DOA in the r th trial. Since there are outliers in $\text{MSE}^{(r)}$ caused by spurious peaks and missing peaks in the MUSIC spectrum, we first exclude the largest 3% and the smallest 3% $\text{MSE}^{(r)}$. Then we calculate the RMSE as the square root of the arithmetic mean of the remaining 94% $\text{MSE}^{(r)}$.

As SNR increases, the RMSE curves of all the arrays decrease. Moreover, HINA has the lowest RMSE among all the arrays for SNR no less than -11 dB. Although the E-FO-Cantor also has a hole-free \mathbb{D}_4 , the U_4 of HINA is 20% larger than that of the E-FO-Cantor, resulting in better DOA estimation performance. On the other hand, while the EAS-NA-NA_{LS} has roughly the same U_4 as HINA, HINA outperforms the EAS-NA-NA_{LS} due to the hole-free \mathbb{D}_4 of HINA.

5. CONCLUDING REMARKS

This paper proposed the half inverted nested array (HINA). Based on the closed-form expression for the optimal parameters, HINA enjoys a hole-free fourth-order difference co-array of size $\mathcal{O}(N^4)$. Numerical examples demonstrated the U_4 of HINA and the improved DOA estimation performance of HINA.

A future direction is to construct new sparse arrays whose hole-free \mathbb{D}_4 is larger than that of HINA [23]. Furthermore, a $2q$ th-order generalization of HINA with a hole-free $2q$ th-order difference co-array of size $\mathcal{O}(N^{2q})$ is also of interest for $q > 2$.

6. REFERENCES

- [1] M. Ibrahim, F. Römer, R. Alieiev, G. Del Galdo, and R. S. Thomä, "On the estimation of grid offsets in CS-based direction-of-arrival estimation," in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2014, pp. 6776–6780.
- [2] L. Pallotta, G. Giunta, and A. Farina, "DOA refinement through complex parabolic interpolation of a sparse recovered signal," *IEEE Signal Processing Letters*, vol. 28, pp. 274–278, 2021.
- [3] T. E. Tuncer and B. Friedlander, *Classical and Modern Direction-of-Arrival Estimation*, Academic Press, Inc., USA, 2009.
- [4] H. L. Van Trees, *Optimum Array Processing: Part IV of Detection, Estimation, and Modulation Theory*, Hoboken, NJ, USA: Wiley, 2002.
- [5] H. Krim and M. Viberg, "Two decades of array signal processing research: the parametric approach," *IEEE Signal Processing Magazine*, vol. 13, no. 4, pp. 67–94, 1996.
- [6] P. Pal and P. P. Vaidyanathan, "Multiple level nested array: An efficient geometry for $2q$ th order cumulant based array processing," *IEEE Transactions on Signal Processing*, vol. 60, no. 3, pp. 1253–1269, 2012.
- [7] S. Shamsunder and G. B. Giannakis, "Modeling of non-gaussian array data using cumulants: Doa estimation of more sources with less sensors," *Signal Processing*, vol. 30, no. 3, pp. 279–297, 1993.
- [8] M.C. Dogan and J.M. Mendel, "Applications of cumulants to array processing .i. aperture extension and array calibration," *IEEE Transactions on Signal Processing*, vol. 43, no. 5, pp. 1200–1216, 1995.
- [9] Y. Zhou, J. Li, W. Nie, and Y. Li, "The fourth-order difference co-array construction by expanding and shift nested array: Revisited and improved," *Signal Processing*, vol. 188, pp. 108198, 2021.
- [10] Q. Shen, W. Liu, W. Cui, S. Wu, and P. Pal, "Simplified and enhanced multiple level nested arrays exploiting high-order difference co-arrays," *IEEE Transactions on Signal Processing*, vol. 67, no. 13, pp. 3502–3515, 2019.
- [11] Y. Zhou, Y. Li, L. Wang, C. Wen, and W. Nie, "The compressed nested array for underdetermined DOA estimation by fourth-order difference coarrays," in *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 4617–4621.
- [12] A. Ahmed, Y. D. Zhang, and B. Himed, "Effective nested array design for fourth-order cumulant-based DOA estimation," in *2017 IEEE Radar Conference (RadarConf)*, 2017, pp. 0998–1002.
- [13] Z. Yang, Q. Shen, W. Liu, Y. C. Eldar, and W. Cui, "Extended Cantor arrays with hole-free fourth-order difference co-arrays," in *2021 IEEE International Symposium on Circuits and Systems (ISCAS)*, 2021, pp. 1–5.
- [14] D. Manolakis, V. Ingle, and S. Kogon, *Statistical and Adaptive Signal Processing: Spectral Estimation, Signal Modeling, Adaptive Filtering and Array Processing*, New York, NY, USA: McGraw-Hill, 2000.
- [15] Q. Shen, W. Liu, W. Cui, and S. Wu, "Extension of nested arrays with the fourth-order difference co-array enhancement," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2016, pp. 2991–2995.
- [16] J. Cai, W. Liu, R. Zong, and Q. Shen, "An expanding and shift scheme for constructing fourth-order difference coarrays," *IEEE Signal Processing Letters*, vol. 24, no. 4, pp. 480–484, 2017.
- [17] P. Pal and P. P. Vaidyanathan, "Nested arrays: A novel approach to array processing with enhanced degrees of freedom," *IEEE Transactions on Signal Processing*, vol. 58, no. 8, pp. 4167–4181, 2010.
- [18] C.-L. Liu and P. P. Vaidyanathan, "Remarks on the spatial smoothing step in coarray music," *IEEE Signal Processing Letters*, vol. 22, no. 9, pp. 1438–1442, 2015.
- [19] V. P. Leonov and A. N. Shiryaev, "On a method of calculation of semi-invariants," *Theory of Probability & Its Applications*, vol. 4, no. 3, pp. 319–329, 1959.
- [20] R. Rajamäki and V. Koivunen, "Sparse symmetric linear arrays with low redundancy and a contiguous sum co-array," *IEEE Transactions on Signal Processing*, vol. 69, pp. 1697–1712, 2021.
- [21] S. Ren, T. Zhu, and J. Liu, "Generalized design approach for fourth-order difference co-array," in *2018 International Conference on Radar (RADAR)*, 2018, pp. 1–5.
- [22] S.U. Pillai, Y. Bar-Ness, and F. Haber, "A new approach to array geometry for improved spatial spectrum estimation," *Proceedings of the IEEE*, vol. 73, no. 10, pp. 1522–1524, 1985.
- [23] Y.-P. Chen and C.-L. Liu, "Half inverted design scheme for large hole-free fourth order difference co-arrays," *In preparation*.