

Hybrid Sparse Array Beamforming Design for General Rank Signal Models

Syed A. Hamza, *Student Member, IEEE* and Moeness G. Amin, *Fellow, IEEE*

Abstract—The paper considers sparse array design for receive beamforming achieving maximum signal-to-interference plus noise ratio (MaxSINR) for both single point source and multiple point sources, operating in an interference active environment. Unlike existing sparse design methods which either deal with structured environment-independent or non-structured environment-dependent arrays, our method is a hybrid approach and seeks a full augmentable array that optimizes beamformer performance. This approach proves important for limited aperture that constrains the number of possible uniform grid points for sensor placements. The problem is formulated as quadratically constraint quadratic program (QCQP), with the cost function penalized with weighted l_1 -norm squared of the beamformer weight vector. Simulation results are presented to show the effectiveness of the proposed algorithms for array configurability in the case of both single and general rank signal correlation matrices. Performance comparisons among the proposed sparse array, the commonly used uniform arrays, arrays obtained by other design methods, and arrays designed without the augmentability constraint are provided.

Index Terms—Sparse arrays, MaxSINR, QCQP, Fully augmentable array, Hybrid array.

I. INTRODUCTION

Sparse array design through sensor selection reduces system receiver overhead by lowering the hardware costs and processing complexity. It finds applications in sensor signal processing for communications, radar, sonar, satellite navigation, radio telescopes, speech enhancement and ultrasonic imaging [3]–[8]. One primary goal in these applications is to determine sensor locations to achieve optimality for some pre-determined performance criteria. This optimality includes minimizing the mean radius of the confidence ellipsoid associated with the estimation error covariance matrix [7], and lowering the Cramer Rao bound (CRB) for angle estimation in direction finding problem [9]. The receiver performance then depends largely on the operating environment, which may change according to the source and interference signals and locations. This is in contrast to sparse arrays whose configurations follow certain formulas and seek to attain high extended aperture co-arrays. The driving objective, in this case, is to enable direction of arrival (DOA) estimation of more sources than physical sensors. Common examples are structured arrays such as nested and coprime arrays [10]–[12].

This work is supported by National Science Foundation (NSF) award no. AST-1547420. This paper was presented in part at the 2019 IEEE International Conference on Acoustics, Speech and Signal Processing, Brighton, U.K., May 2019 [1] and 2018 IEEE Radar Conference, Oklahoma City, USA, April 2018 [2]. (Corresponding author: Syed A. Hamza.)

The authors are with the Center for Advanced Communications (CAC), College of Engineering, Villanova University, PA 19085-1681 USA (e-mails: shamza@villanova.edu, moeness.amin@villanova.edu).

Sparse array design typically involves the selection of a subset of uniform grid points for sensor placements. For a given number of sensors, it is often assumed that the number of grid points, spaced by half wavelength, is unlimited. However, in many applications, there is a constraint on the spatial extent of the system aperture. In this case, a structured array, in seeking to maximize the number of spatial autocorrelation lags, may find itself placing sensors beyond the available physical aperture. The problem then becomes that of dual constraints, one relates to the number of sensors, and the other to the number of grid-points.

With a limited aperture constraint invoked, few sensors may in fact be sufficient to produce a desirable filled structured co-array, even with narrowband assumption and without needing wideband or multiple frequencies [13]. In this case, any additional sensors, constitute a surplus that can be utilized to meet an environment-dependent performance criterion, such as maximum signal-to-interference and noise ratio (SINR). Thereby, one can in essence reap the benefits of structured and non-structured arrays. This paradigm calls for a new aperture design approach that strives to provide filled co-arrays and, at the same time, be environment-sensitive. This hybrid design approach is the core contribution of this paper.

Sparse sensor design has thoroughly been studied to economize the receive beamformer [14]–[27]. However, in contrast to MaxSINR design, the main focus of the efforts, therein, was in achieving desirable beampattern characteristics with nominal sidelobe levels, since the sparse beamformer is susceptible to high sidelobe levels. For example, an array thinning design was proposed for sidelobe minimization in [18] by starting from a fully populated array and sequentially removing sensors in a systematic manner. Instead, the sparse array design presented in [19] to optimize the peak sidelobe level involves a joint design of sensor locations and their corresponding beamforming weights. A beampattern matching design explained in [20] can effectively recover sparse topologies through an iterative cyclic approach. Additionally, global optimization tools such as Genetic Algorithms/Simulated Annealing and convex relaxation schemes based on re-weighted l_1 -norm minimization have been rigorously exploited in sensor selection problem for synthesizing a user-specified receive beampattern response [22]–[27].

In environment-dependent array design, signal power estimation and enhancement in an interference active environment has a direct bearing on improving target detection and localization for radar signal processing, increasing throughput or channel capacity for MIMO wireless communication systems, and enhancing resolution capability in medical imaging [28]–[30].

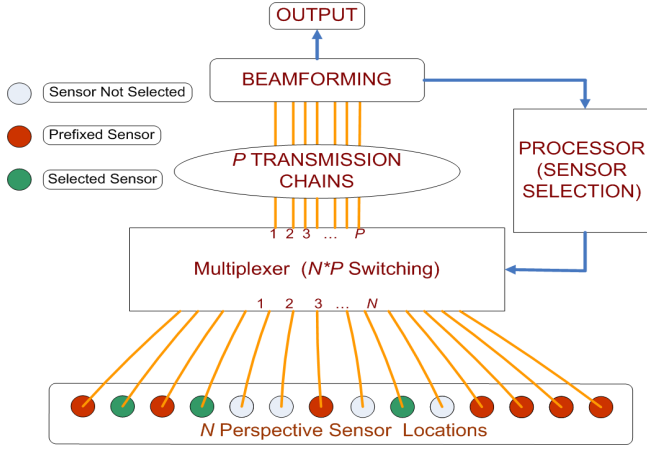


Fig. 1: Block diagram of adaptive switched sensor beamformer

It is noted that with sparse array, the commonly used Capon beamforming must not only find the optimum weights but also the optimum array configuration. This is clearly an entwined optimization problem, and requires finding maximum SINR over all possible sparse array configurations. Maximum signal to noise ratio (MaxSNR) and MaxSINR have been shown to yield significantly efficient beamforming with performance depending mainly on the positions of the sensors as well as the locations of sources in the field of view (FOV) [31]–[33].

In this paper, we consider a bi-objective optimization problem, namely achieving the filled co-array and maximizing the SINR. The proposed technique enjoys key advantages as compared to state-of-the-art sparse aperture design, namely, (a) It does not require any *a priori* knowledge of the jammers directions of arrival and their respective power which is implicitly assumed in previous contributions [34]–[36]. As such, it is possible to directly work on the received data correlation matrix (b) It extends to spatial spread sources in a straightforward way.

The proposed hybrid approach first determines a prefixed sparse array that results in a filled co-array with minimum number of sensors. This prefixed configuration could be a minimum redundancy array (MRA) [10], nested or coprime array configuration that fills the aperture under consideration with minimal sensors, allowing maximum degrees of freedom for SINR maximization. This prefixed sensor configuration can be achieved by an optimization problem involving the minimum number of sensors spanning a pre-determined aperture. However, for the scope of this paper, the prefixed configuration is set by MRA or other structured arrays. The remaining sensors after forming the prefixed array are utilized to maximize the SINR. The cascade nature of the proposed hybrid approach is relatively simpler than the ultimate design approach that produces the optimum filled sparse array that maximizes SINR. Environment-dependent array design lowers the hardware complexity by reducing the expensive transmission chains through sensor switching as shown in the block diagram in Fig. 1. The proposed hybrid approach, however, has an added advantage of offering a simplified sensor switching in time-varying environment. This is attributed to large number

of fixed location sensors which would always remain non-switched, irrespective of the sources and interferences in the FOV.

The proposed hybrid approach is particularly permissive as the number N of possible sensor locations increases. To further clarify, it is noted that sparse arrays having N available sensors can typically span a filled array aperture of the order of $\mathcal{O}(N(N-1)/2)$ [11]; conversely, given an aperture spanning N possible sensor locations, only $\mathcal{O}(N^{1/2})$ sensors are sufficient to synthesize a fully augmentable array design. This emphasizes the fact that as the possible aperture size increases, then relatively few sensors are required to meet the full augmentability condition, leaving more degrees of freedom to optimize for SINR enhancement. The hybrid approach also lends itself to more desirable beampattern characteristics by maintaining minimum spacing between sensor elements. It is important to note that having fully augmentable arrays not only provide the benefits of simplified sensor switching and improved identifiability of large number of sources, but also they ensure the availability of full array data covariance matrix essential to carry optimized SINR configuration [37], [38]. Therefore, the proposed simplified hybrid sensor switching architecture ensures the knowledge of global data statistics at all times, in contrast to previous efforts in [39]–[41] that sort to optimize data dependent microphone placement viz a viz transmission power. The proposed methodology therein targets a different objective function and primarily relies on local heuristics. In this case, sensor switching comes with an additional implementation overhead, in an attempt to recursively match the performance offered by the knowledge of global statistics.

We consider the problem of MaxSINR sparse arrays with limited aperture for both single and higher rank signal correlation matrices. The case of single rank correlation matrix arises when there is one desired source signal in the FOV, whereas the case of higher rank signal model occurs for spatially spread source. The problem is posed as optimally selecting P sensors out of N possible equally spaced grid points. Maximizing SINR amounts to maximizing the principal eigenvalue of the product of the inverse of data correlation matrix and the desired source correlation matrix [42]. Since it is an NP hard optimization problem, we pose this problem as QCQP with weighted l_1 -norm squared to promote sparsity. The re-weighted l_1 -norm squared relaxation is effective for reducing the required sensors and minimizing the transmit power for multicast beamforming [4]. We propose a modified re-weighting matrix based iterative approach to control the sparsity of the optimum weight vector so that P sensor fully augmentable hybrid array is finally selected. This modified regularization re-weighting matrix based approach incorporates the prefixed structured array assumption in our design and works by minimizing the objective function around the presumed prefixed array.

The rest of the paper is organized as follows: In the next section, we state the problem formulation for maximizing the output SINR under general rank signal correlation matrix. Section III deals with the optimum sparse array design by semidefinite relaxation (SDR) and proposed modified re-

weighting based iterative algorithm of finding P sensor fully augmentable hybrid sparse array design. In section IV, with the aid of number of design examples, we demonstrate the usefulness of fully augmentable arrays achieving MaxSINR and highlight the effectiveness of the proposed methodology for sparse array design. Concluding remarks follow at the end.

II. PROBLEM FORMULATION

Consider K desired sources and L independent interfering source signals impinging on a linear array with N uniformly placed sensors. The baseband signal received at the array at time instant t is then given by;

$$\mathbf{x}(t) = \sum_{k=1}^K (\alpha_k(t)) \mathbf{s}(\theta_k) + \sum_{l=1}^L (\beta_l(t)) \mathbf{v}(\theta_l) + \mathbf{n}(t), \quad (1)$$

where, $\mathbf{s}(\theta_k)$ and $\mathbf{v}(\theta_l) \in \mathbb{C}^N$ are the corresponding steering vectors respective to directions of arrival, θ_k or θ_l , and are defined as follows;

$$\mathbf{s}(\theta_k) = [1 \ e^{j(2\pi/\lambda)d\cos(\theta_k)} \dots e^{j(2\pi/\lambda)d(N-1)\cos(\theta_k)}]^T. \quad (2)$$

The inter-element spacing is denoted by d , $(\alpha_k(t), \beta_l(t)) \in \mathbb{C}$ denote the complex amplitudes of the incoming baseband signals [43]. The additive Gaussian noise $\mathbf{n}(t) \in \mathbb{C}^N$ has a variance of σ_n^2 at the receiver output. The received signal vector $\mathbf{x}(t)$ is combined linearly by the N -sensor beamformer that strives to maximize the output SINR. The output signal $y(t)$ of the optimum beamformer for maximum SINR is given by [42],

$$y(t) = \mathbf{w}_o^H \mathbf{x}(t), \quad (3)$$

where \mathbf{w}_o is the solution of the optimization problem given below;

$$\begin{aligned} & \underset{\mathbf{w} \in \mathbb{C}^N}{\text{minimize}} \quad \mathbf{w}^H \mathbf{R}_s \mathbf{w}, \\ & \text{s.t.} \quad \mathbf{w}^H \mathbf{R}_s \mathbf{w} = 1. \end{aligned} \quad (4)$$

For statistically independent signals, the desired source correlation matrix is given by, $\mathbf{R}_s = \sum_{k=1}^K \sigma_k^2 \mathbf{s}(\theta_k) \mathbf{s}^H(\theta_k)$, where, $\sigma_k^2 = E\{\alpha_k(t) \alpha_k^H(t)\}$. Likewise, we have the interference and noise correlation matrix $\mathbf{R}_{s'} = \sum_{l=1}^L (\sigma_l^2 \mathbf{v}(\theta_l) \mathbf{v}^H(\theta_l)) + \sigma_n^2 \mathbf{I}_{N \times N}$, with $\sigma_l^2 = E\{\beta_l(t) \beta_l^H(t)\}$ being the power of the l th interfering source. The problem in (4) can be written equivalently by replacing $\mathbf{R}_{s'}$ with the received data covariance matrix, $\mathbf{R}_{xx} = \mathbf{R}_s + \mathbf{R}_{s'}$ as follows [42],

$$\begin{aligned} & \underset{\mathbf{w} \in \mathbb{C}^N}{\text{minimize}} \quad \mathbf{w}^H \mathbf{R}_{xx} \mathbf{w}, \\ & \text{s.t.} \quad \mathbf{w}^H \mathbf{R}_s \mathbf{w} \geq 1. \end{aligned} \quad (5)$$

It is noted that the equality constraint in (4) is relaxed in (5) due to the inclusion of the constraint as part of the objective function, and as such, (5) converges to the equality constraint. Additionally, the optimal solution in (5) is invariant up to uncertainty of the absolute powers of the sources of interest. Accordingly, the relative power profile of the sources of interest would suffice. For a single desired point source, this implies that only the knowledge of the DOA of the desired source is sufficient rather than the exact knowledge of the desired source correlation matrix. Similarly, neither the source

power nor the average power of the scatterers is required in (5) for spatially spread sources when the spatial channel model, such as the Gaussian or circular, is assumed [44]. However, in practice, these assumptions can deviate from the actual received data statistics and hence the discrepancy is typically mitigated, to an extent, by preprocessing the received data correlation matrix through diagonal loading or tapering the correlation matrix [30].

There exists a closed form solution of the above optimization problem and is given by $\mathbf{w}_o = \mathcal{P}\{\mathbf{R}_s^{-1} \mathbf{R}_s\} = \mathcal{P}\{\mathbf{R}_{xx}^{-1} \mathbf{R}_s\}$. The operator $\mathcal{P}\{\cdot\}$ computes the principal eigenvector of the input matrix. Substituting \mathbf{w}_o into (3) yields the corresponding optimum output SINR_o;

$$\text{SINR}_o = \frac{\mathbf{w}_o^H \mathbf{R}_s \mathbf{w}_o}{\mathbf{w}_o^H \mathbf{R}_{s'} \mathbf{w}_o} = \Lambda_{max}\{\mathbf{R}_s^{-1} \mathbf{R}_s\}. \quad (6)$$

This shows that the optimum output SINR_o is given by the maximum eigenvalue (Λ_{max}) associated with the product of the inverse of interference plus noise correlation matrix and the desired source correlation matrix. Therefore, the performance of the optimum beamformer for maximizing the output SINR is directly related to the desired and interference plus noise correlation matrix. It is to be noted that the rank of the desired source signal correlation matrix equals K , i.e. the cardinality of the desired sources.

III. OPTIMUM SPARSE ARRAY DESIGN

The problem of locating the maximum principal eigenvalue among all the correlation matrices associated with P sensor selection is a combinatorial optimization problem. The constraint optimization (5) can be re-formulated for optimum sparse array design by incorporating an additional constraint on the cardinality of the weight vector;

$$\begin{aligned} & \underset{\mathbf{w} \in \mathbb{C}^N}{\text{minimize}} \quad \mathbf{w}^H \mathbf{R}_{xx} \mathbf{w}, \\ & \text{s.t.} \quad \mathbf{w}^H \mathbf{R}_s \mathbf{w} \geq 1, \\ & \quad \|\mathbf{w}\|_0 = P. \end{aligned} \quad (7)$$

Here, $\|\cdot\|_0$ determines the cardinality of the weight vector \mathbf{w} . We assume that we have an estimate of all the filled co-array correlation lags corresponding to the correlation matrix of the full aperture array. The problem expressed in (7) can be relaxed to induce the sparsity in the beamforming weight vector \mathbf{w} without placing a hard constraint on the specific cardinality of \mathbf{w} , as follows [45];

$$\begin{aligned} & \underset{\mathbf{w} \in \mathbb{C}^N}{\text{minimize}} \quad \mathbf{w}^H \mathbf{R}_{xx} \mathbf{w} + \mu(\|\mathbf{w}\|_1), \\ & \text{s.t.} \quad \mathbf{w}^H \mathbf{R}_s \mathbf{w} \geq 1. \end{aligned} \quad (8)$$

Here, $\|\cdot\|_1$ is the sparsity inducing l_1 -norm and μ is a parameter to control the desired sparsity in the solution. Even though the relaxed problem expressed in (8) is not exactly similar to that of (7), yet it is well known that l_1 -norm regularization has been an effective tool for recovering sparse solutions in many diverse formulations [46]–[48]. The problem in (8) can

be penalized instead by the weighted l_1 -norm function which is a well known sparsity promoting formulation [49],

$$\begin{aligned} & \underset{\mathbf{w} \in \mathbb{C}^N}{\text{minimize}} \quad \mathbf{w}^H \mathbf{R}_{xx} \mathbf{w} + \mu (||(\mathbf{b}^i \circ |\mathbf{w}|)||_1), \\ & \text{s.t.} \quad \mathbf{w}^H \mathbf{R}_s \mathbf{w} \geq 1. \end{aligned} \quad (9)$$

where, “ \circ ” denotes the element wise product, “ $|\cdot|$ ” is the modulus operator and $\mathbf{b}^i \in \mathbb{R}^N$ is the regularization re-weighting vector at the i th iteration. Therefore, (9) is the sequential optimization methodology, where the regularization re-weighting vector \mathbf{b}^i is typically chosen as an inverse function of the beamforming weight vector obtained at the previous iteration. This, in turn, suppresses the sensors corresponding to smaller beamforming weights, thereby encouraging sparsity in an iterative fashion. The weighted l_1 -norm function in (9) is replaced by the l_1 -norm squared function which does not alter the regularization property of the weighted l_1 -norm function [4],

$$\begin{aligned} & \underset{\mathbf{w} \in \mathbb{C}^N}{\text{minimize}} \quad \mathbf{w}^H \mathbf{R}_{xx} \mathbf{w} + \mu (||(\mathbf{b}^i \circ |\mathbf{w}|)||_1^2), \\ & \text{s.t.} \quad \mathbf{w}^H \mathbf{R}_s \mathbf{w} \geq 1. \end{aligned} \quad (10)$$

The semidefinite formulation (SDP) of the above problem can then be realized by re-expressing the quadratic form, $\mathbf{w}^H \mathbf{R}_{xx} \mathbf{w} = \text{Tr}(\mathbf{w}^H \mathbf{R}_{xx} \mathbf{w}) = \text{Tr}(\mathbf{R}_{xx} \mathbf{w} \mathbf{w}^H) = \text{Tr}(\mathbf{R}_{xx} \mathbf{W})$, where $\text{Tr}(\cdot)$ is the trace of the matrix. Similarly, the regularization term $||(\mathbf{b}^i \circ |\mathbf{w}|)||_1^2 = (|\mathbf{w}|^T \mathbf{b}^i)((\mathbf{b}^i)^T |\mathbf{w}|) = |\mathbf{w}|^T \mathbf{B}^i |\mathbf{w}| = \text{Tr}(\mathbf{B}^i |\mathbf{W}|)$. Here, $\mathbf{W} = \mathbf{w} \mathbf{w}^H$ and $\mathbf{B}^i = \mathbf{b}^i (\mathbf{b}^i)^T$ is the regularization re-weighting matrix at the i th iteration. Utilizing these quadratic expressions in (10) yields the following problem [2], [4], [50],

$$\begin{aligned} & \underset{\mathbf{W} \in \mathbb{C}^{N \times N}, \tilde{\mathbf{W}} \in \mathbb{R}^{N \times N}}{\text{minimize}} \quad \text{Tr}(\mathbf{R}_{xx} \mathbf{W}) + \mu \text{Tr}(\mathbf{B}^i \tilde{\mathbf{W}}), \\ & \text{s.t.} \quad \text{Tr}(\mathbf{R}_s \mathbf{W}) \geq 1, \\ & \quad \tilde{\mathbf{W}} \geq |\mathbf{W}|, \\ & \quad \mathbf{W} \succeq 0, \text{Rank}(\mathbf{W}) = 1. \end{aligned} \quad (11)$$

The function “ $|\cdot|$ ” returns the absolute values of the entries of the matrix, “ \geq ” is the element wise comparison and “ \succeq ” denotes the generalized matrix inequality. The auxiliary matrix $\tilde{\mathbf{W}} \in \mathbb{R}^{N \times N}$ implements the weighted l_1 -norm squared regularization along with the re-weighting matrix \mathbf{B}^i . The rank constraint in (11) is non convex and therefore need to be removed. The rank relaxed approximation works well for the underlying problem. In case, the solution matrix is not rank 1, we can resort to randomization to harness rank 1 approximate solutions [51]. Alternatively, one could minimize the nuclear norm of \mathbf{W} , as a surrogate for l_1 -norm in the case of matrices, to induce sparsity in the eigenvalues of \mathbf{W} and promote rank one solutions [52], [53]. The resulting rank relaxed semidefinite program (SDR) is given by;

$$\begin{aligned} & \underset{\mathbf{W} \in \mathbb{C}^{N \times N}, \tilde{\mathbf{W}} \in \mathbb{R}^{N \times N}}{\text{minimize}} \quad \text{Tr}(\mathbf{R}_{xx} \mathbf{W}) + \mu \text{Tr}(\mathbf{B}^i \tilde{\mathbf{W}}), \\ & \text{s.t.} \quad \text{Tr}(\mathbf{R}_s \mathbf{W}) \geq 1, \\ & \quad \tilde{\mathbf{W}} \geq |\mathbf{W}|, \\ & \quad \mathbf{W} \succeq 0. \end{aligned} \quad (12)$$

In general, QCQP is NP hard and cannot be solved in polynomial time. The formulation in (12) is clearly convex,

in terms of unknown matrices, as all the other correlation matrices involved are guaranteed to be positive semidefinite. The sparsity parameter μ largely determines the cardinality of the solution beamforming weight vector. To ensure P sensor selection, appropriate value of μ is typically found by carrying a binary search over the probable range of μ . After achieving the desired cardinality, the reduced size thinned correlation matrix \mathbf{R}_{xx} is formed corresponding to the non-zero values of $\tilde{\mathbf{W}}$. The reduced dimension SDR is now solved with setting $\mu = 0$, yielding optimum beamformer $\mathbf{w}_o = \mathcal{P}\{\mathbf{W}\}$.

A. Fair gain beamforming

The optimization in (12) strives to incorporate the signal from all the directions of interest while optimally removing the interfering signals. To achieve this objective, the optimum sparse array may show leaning towards a certain source of interest, consequently, not offering fair gain towards all sources. In an effort to promote equal gain towards all sources, we put a separate constraint on the power towards all desired sources as follows;

$$\begin{aligned} & \underset{\mathbf{W} \in \mathbb{C}^{N \times N}, \tilde{\mathbf{W}} \in \mathbb{R}^{N \times N}}{\text{minimize}} \quad \text{Tr}(\mathbf{R}_{xx} \mathbf{W}) + \mu \text{Tr}(\mathbf{B}^i \tilde{\mathbf{W}}), \\ & \text{s.t.} \quad \text{Tr}(\mathbf{R}_k \mathbf{W}) \geq 1, \quad \forall k \in (1, 2, 3 \dots K) \\ & \quad \tilde{\mathbf{W}} \geq |\mathbf{W}|, \\ & \quad \mathbf{W} \succeq 0. \end{aligned} \quad (13)$$

Here, $\mathbf{R}_k = \mathbf{s}(\theta_k) \mathbf{s}^H(\theta_k)$ is the rank 1 covariance matrix associated with the source at DOA (θ_k). However, the above SDR can be solved to an arbitrary small accuracy ζ , by employing interior point methods involving the worst case complexity of $\mathcal{O}\{\max(K, N)^4 N^{(1/2)} \log(1/\zeta)\}$ [51].

B. Modified re-weighting for fully augmentable hybrid array

For the case without the full augmentability constraint the regularization re-weighting matrix \mathbf{B} is initialized unweighted i.e. by all ones matrix and the m, n th element of \mathbf{B} is iteratively updated as follows [49],

$$\mathbf{B}_{m,n}^{i+1} = \frac{1}{|\mathbf{W}_{m,n}^i| + \epsilon}. \quad (14)$$

The parameter ϵ avoids the unwanted case of division by zero, though its choice is fairly independent to the performance of the iterative algorithm but at times very small values of ϵ can result in the algorithm getting trapped in the local minima. For the hybrid array design, we initialize the re-weighting matrix instead as an outer product of hybrid selection vector \mathbf{z} . The hybrid selection vector \mathbf{z} is an N dimensional vector containing binary entries of zero and one, where, zeros correspond to the pre-selected sensors and ones correspond to the remaining sensors to be selected. Hence, the cardinality of \mathbf{z} is equal to the difference of the total number of available sensors and the number of pre-selected sensors. This modified re-weighting approach ensures that the sensors corresponding to the pre-selected configuration is not penalized as part of the regularization, hence, $\mathbf{B} = \mathbf{z} \mathbf{z}^T$, thrives solutions that incorporate the

Algorithm 1 Proposed algorithm to achieve desired cardinality of optimal weight vector \mathbf{w}_o .

Input: Data correlation matrix $\mathbf{R}_{\mathbf{x}\mathbf{x}}$, N , P , look direction DOA's θ_k , hybrid selection vector \mathbf{z} .

Output: P sensor beamforming weight vector \mathbf{w}_o , Initialize ϵ .

Initialize μ_{lower} , μ_{upper} (Initializing lower and upper limits of sparsity parameter range for binary search for desired cardinality P)

FSDR: Initialize $\mathbf{B} = \mathbf{z}\mathbf{z}^T$.

NFSDR: For optimum array design without the augmentability constraint, initialize \mathbf{z} to be all ones vector, $\mathbf{B} = \mathbf{z}\mathbf{z}^T$ (all ones matrix).

Perturbed-NFSDR: Locate the sensor i such that, if not selected, results in the minimum compromise of the objective function. Perturb \mathbf{z} at position i , $\mathbf{z}(i) = \mathbf{z}(i) + \gamma$, afterwards calculating $\mathbf{B} = \mathbf{z}\mathbf{z}^T$.

while (Cardinality of $\mathbf{w}_o \neq P$) **do**

Update μ through binary search.

for (Typically requires five to six iterations) **do**

Run the SDR of (12) or (13) (Fair gain case).

Update the regularization weighting matrix \mathbf{B} according to (15).

end for

end while

After achieving the desired cardinality, run SDR for reduced size correlation matrix corresponding to nonzero values of $\tilde{\mathbf{W}}$ and $\mu = 0$, yielding, $\mathbf{w}_o = \mathcal{P}\{\mathbf{W}\}$.

return \mathbf{w}_o

pre-selected array topology. The modified penalizing weight update for the hybrid array design can be expressed as;

$$\mathbf{B}^{i+1} = (\mathbf{z}\mathbf{z}^T) \oslash (|\mathbf{W}^i| + \epsilon). \quad (15)$$

The symbol “ \oslash ” denotes element wise division. For the hybrid design, (15) is proposed with appropriate selection of \mathbf{z} , as explained above, and hereafter referred to as the Fixed SDR (FSDR). The array designed without the augmentability consideration is the special case of (15) with \mathbf{z} being an all ones vector and the algorithm is subsequently regarded as the Non-Fixed SDR (NFSDR). The pseudo-code for controlling the sparsity of the optimal weight vector \mathbf{w}_o is summarized in **Algorithm 1**.

C. Symmetric arrays

The solution of the NFSDR formulation is penchant for symmetric arrays in the case of symmetric initialization vector \mathbf{z} . The plausible explanation is as follows. We first show that the beamforming weights which maximizes the output SINR for symmetric sparse array topologies are conjugate symmetric w.r.t. the array center.

Proposition 1. *The conjugate symmetry of the optimal weight vector holds for centro-symmetric sparse array configurations in case of the general rank desired source model.*

Proof. (Refer to the Appendix for the proof.) ■

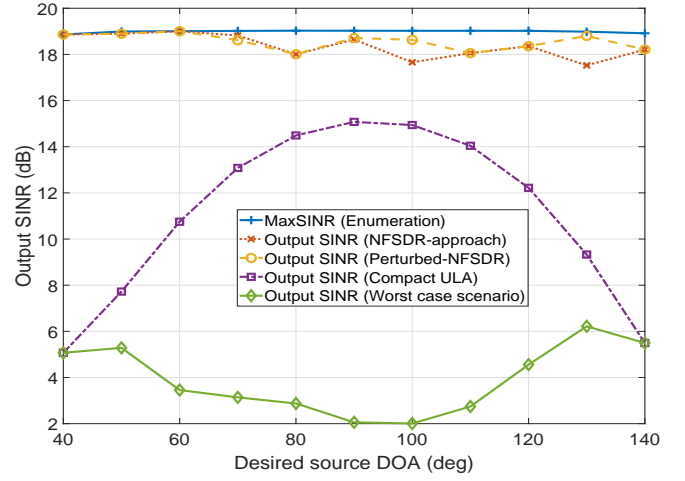


Fig. 2: Output SINR for different array topologies

We observe that the regularized cost function does not invoke sparsity until after the first few initial iterations. Consequently, the initial solutions of the semidefinite program has symmetric coefficients as the NFSDR seeks near optimal solutions which are analytically shown to be conjugate symmetric. Moreover, the iterative sparsity enhancing formulation introduces sparsity by penalizing the beamforming weight vector according to (15), where, it only accounts the magnitude of the beamforming weights. Therefore, at each iteration the regularization re-weighting matrix \mathbf{B} happens to penalize the solution weight vector in a symmetric fashion around the array center. Thus, the iterative NFSDR sparse solution favors symmetric configurations by discarding corresponding symmetric sensors simultaneously. Though, the symmetric configuration can be suitable for certain applications [54], and can have desirable performance, yet, it reduces the available degrees of freedom. Therefore, to avoid curtailing the available degrees of freedom, we perturb the re-weighting regularization matrix \mathbf{B} at the initial iteration, as follows. From N prospective locations, find the sensor position, which if not selected, results in the least compromise of the objective function performance. Corresponding to the aforementioned position, set the regularization weight to be relatively high through perturbation by parameter γ . By so doing, we resolve the issues arising from the symmetric regularization re-weighting matrix. This modified algorithm is henceforth referred to as the perturbed-NFSDR and is detailed in **Algorithm 1**.

IV. SIMULATIONS

In this section, we show the effectiveness of the proposed techniques for the sparse array design for MaxSINR. We initially examine the proposed approach for array configurability by considering arbitrary arrays without the augmentability constraint. In the later examples, we demonstrate the effectiveness of fully augmentable hybrid sparse array design through linear and 2D arrays. We focus on the EM modality, and as such we use antennas for sensors.

A. Single point source

We select $P = 8$ antennas from $N = 16$ possible equally spaced locations with inter-element spacing of $\lambda/2$. Figure 2 shows the output SINR for different array configurations for the case of single desired point source with its DOA varying from 40° to 140° . The interfering signals are located at 20° and $\pm 10^\circ$ degree apart from the desired source angle. To explain this scenario, suppose that the desired source is at 60° , we consider the respective directions of arrival of the three interfering signals at 40° , 50° and 70° . The SNR of the desired signal is 10 dB, and the interference to noise ratio (INR) is set to 10 dB for each scenario. The input SINR is -4.9 dB. The upper and lower limit of the sparsity parameter μ is set to 1.5 and 0.01 respectively, $\gamma = 0.05$ and $\epsilon = 0.1$. From the Fig. 2, it is evident that the NFSDR-approach performs close to the performance of the optimum array found by exhaustive search (12870 possible configurations), which has very high computational cost attributed to expensive singular value decomposition (SVD) for each enumeration. Moreover, the perturbed-NFSDR algorithm results in comparable or better performance. Except for the slightly lower performance at the desired source of DOA of 70° , we observe that for the desired source of DOA at 90° , 100° and 130° , the perturbed-NFSDR recovers a sparse array with better performance than the NFSDR-approach. For the other DOAs, the perturbed-NFSDR recovers the same symmetric configuration as that recovered by the NFSDR-approach. This emphasizes that the perturbed-NFSDR does not eliminate the possibility of symmetric solutions and optimizes over both the symmetrical and unsymmetrical array configurations. On average, the proposed algorithms takes six to seven iterations to converge to the optimum antenna locations; hence, offering considerable savings in the computational cost. It is of interest to compare the optimum sparse array performance with that of compact uniform linear array (ULA). It can be seen from Fig. 2, that the optimum sparse array offers considerable SINR advantage over the compact ULA for all source angles of arrival. The ULA performance degrades severely when the source of interest is more towards the array end-fire location. In this case, the ULA fails to resolve and cancel the strong interferers as they are located close to the desired source.

For the case of the desired source at the array broadside, the maximum output SINR of the optimum array found through enumeration (Fig. 4a) is 19 dB. The optimum array design obtained through the NFSDR-approach yields an output SINR of 18.6 dB, which is 0.4 dB less than the corresponding SINR of the optimum array found through exhaustive search. The broadside source arrays are shown in the Fig. 4 (where green-filled circle indicates antenna present whereas gray-filled circle indicates antenna absent). The sparse array recovered through NFSDR-approach is clearly a symmetric configuration (Fig. 4b). Figure 4c shows the sparse array found after addressing the symmetry bias by the approach explained in Section III-C. The SINR for this non-symmetric configuration is 18.7 dB and is suboptimal merely by 0.3 dB. It is worth noticing that the worst performing sparse array configuration (Fig. 4d) comparatively engages larger array aperture than the optimum

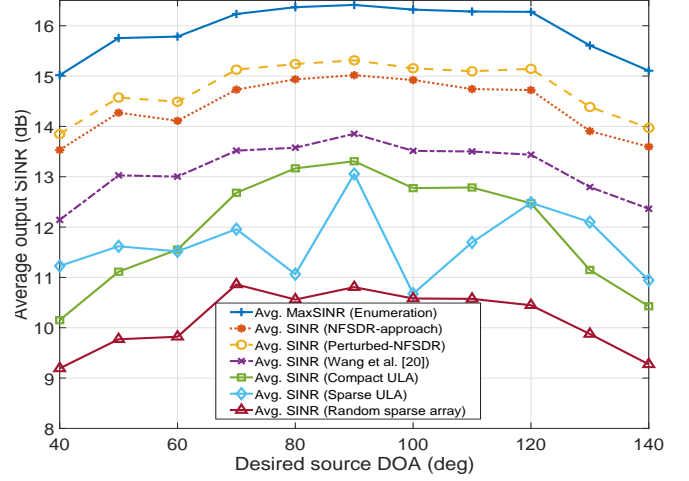


Fig. 3: Average Output SINR for different array topologies over 6000 Monte Carlo trials

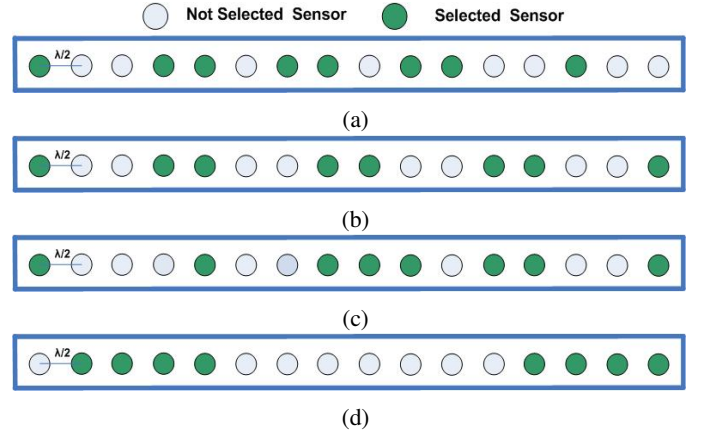


Fig. 4: Array configurations obtained for the point source at the array broadside (a) Optimum (Enumeration) (b) NFSDR-approach (c) Perturbed-NFSDR (d) Worst performing array configuration

array found through enumeration (Fig. 4a), yet it has an output SINR as low as 2.06 dB. This emphasizes the fact that if an arbitrary sparse array structure is employed, it could degrade the performance catastrophically irrespective of the occupied aperture and could perform far worst than the compact ULA, which offers modest output SINR of 15.07 dB for the scenario under consideration.

1) *Monte Carlo Simulation:* To thoroughly examine the performance of the proposed algorithms under random interfering environments, we perform 6000 Monte Carlo simulations. For this purpose, the desired source DOA is fixed with SNR of 10 dB, and eight interferences are generated which are uniformly distributed anywhere from 20° to 160° . The INRs of these sources are uniformly drawn from 10 dB to 15 dB. We choose 8 antennas out of 16 possible locations. The upper and lower limit of the sparsity parameter μ is set to 3 and 0.01 respectively, $\gamma = 0.1$ and $\epsilon = 0.05$. The performance curves are shown in Fig. 3 for the desired source fixed at 11 different DOAs varying from 40° to 140° . On average, the

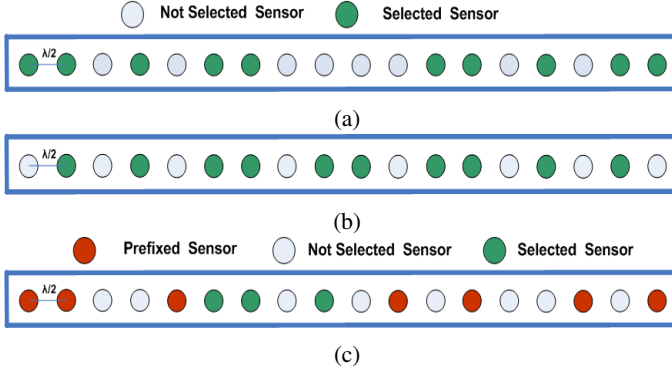


Fig. 5: (a) Antenna array multiple sources (NFSDR-approach) (b) Fair gain 10 element antenna array (NFSDR-approach) (c) Hybrid 10 antenna array for multiple desired sources (FSDR)

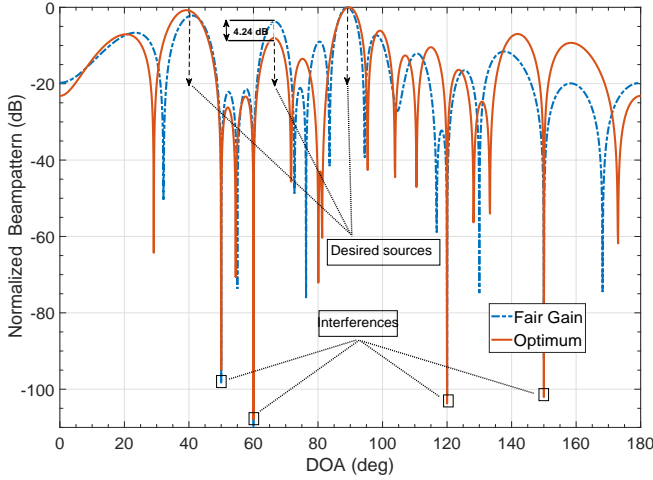


Fig. 6: Beampattern for multiple point sources

proposed perturbed-NFSDR algorithm consistently provided superior SINR performance. However, this performance is around 1.2 dB suboptimal than the average SINR computed through enumeration. The average SINR performance of the perturbed-NFSDR algorithm is around 0.35 dB better than the proposed NFSDR-approach. This is because the degrees of freedom are limited by the inherent array symmetry enforced by the re-weighted optimization scheme. The performances of the proposed algorithms are compared with the design methodology proposed in [35], which relies on the *a priori* knowledge of the interference steering vectors and respective powers. It is noted that in the underlying scenario the design in [35] is more than 1 dB suboptimal than the proposed algorithms and around 2 dB suboptimal as compared to the performance upper bound. The algorithm in [35] relies on successive linear approximation of the objective function as opposed to the quadratic implementation of the SDR, thereby suffering in performance. The SINR performances for the compact ULA, sparse ULA and randomly employed sparse topology are also shown in the Fig. 3, further highlighting the utility of sparse array design.

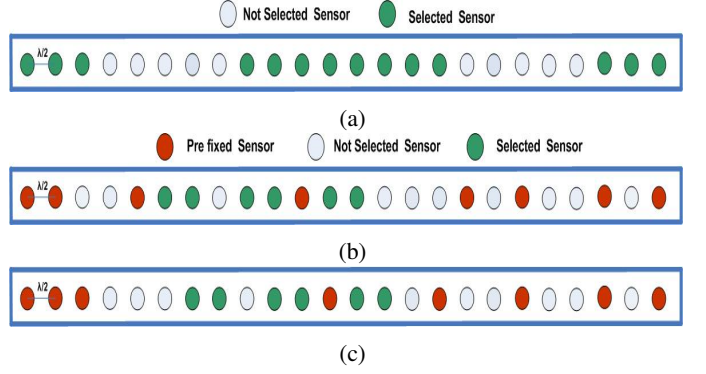


Fig. 7: (a) 14 element antenna array (NFSDR-approach) (b) Hybrid 14 antenna sparse array (8 prefixed, 6 selected through FSDR) (c) Hybrid 14 antenna sparse array (8 prefixed, 6 selected through FSDR)

B. Multiple point sources

For the multiple point sources scenario, consider three desired signals impinging from DOAs 40° , 65° and 90° with SNR of 0 dB each. Unlike the example in IV-A, we set four strong interferers with INR of 30 dB are operational at DOAs 50° , 60° , 120° and 150° . In so doing, we analyze the robustness of the proposed scheme under very low input SINR of -36.02 dB. We select 10 antennas out of 18 available slots. The optimum array recovered through convex relaxation is shown in Fig. 5a. This configuration results with an output SINR of 11.85 dB against SINR of 12.1 dB for the optimum configuration found through enumeration. For the fair gain beamforming, we apply the optimization of (13) and the array configuration for MaxSINR for the fair gain beamforming is shown in Fig 5b. The output SINR for the fair beamforming case is 11.6 dB which is slightly less than the optimum array without the fair gain consideration (11.85 dB). However, the advantage of fair beamforming is well apparent from the beampatterns in both cases as shown in Fig 6, where the gain towards the source at 65° is around 4.24 dB higher than the case of optimum array without the fair gain consideration. The maximum gain deviation for the fair gain case is 3.5 dB vs. 8 dB variation without the fair gain consideration. The SINR of compact ULA is compromised more than 3 dB as compared to the optimum sparse array (Fig. 5a) obtained through the proposed methodology. This improved performance is due to the optimum sparse array smartly engaging its degrees of freedom to eradicate the interfering signals while maintaining maximum gain towards all sources of interest.

C. Fully augmentable linear arrays

Consider selecting 14 antennas out of 24 possible available locations with antenna spacing of $\lambda/2$. A desired source is impinging from DOA of 30° and SNR of 10 dB, whereas narrowband jammers are operating at 20° , 40° and 120° with INR of 10 dB each. The range of μ and other parameters are the same as in IV-A1. Optimum array configuration (Fig. 7a) achieved through convex relaxation (NFSDR-approach) has an output SINR of 21.29 dB as compared to SINR of 21.32 dB

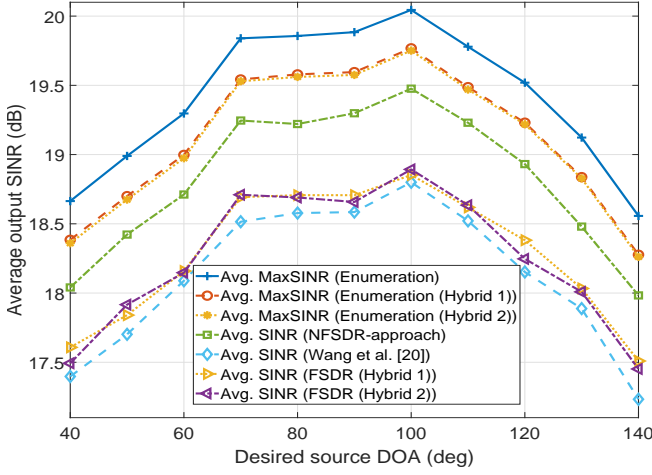


Fig. 8: Average Output SINR for different array topologies over 3500 Monte Carlo trials

of an optimum array recovered through enumeration (1.96×10^6 possible configurations). It should be noted that the array recovered without filled co-array constraint is not essentially fully augmentable as is the case in the optimum array (Fig. 7a) which clearly has missing co-array lags.

In quest of fully augmentable array design we prefix 8 antennas (red elements in Fig. 7b) in a minimum redundancy array (MRA) configuration over 24 uniform grid points. This provides 24 consecutive autocorrelation lags. We are, therefore, left with six antennas to be placed in the remaining 16 possible locations (8008 possible configurations). We enumerated the performance of all possible hybrid arrays associated with underlying MRA configuration and found the output SINR ranges from 18.1 dB to 21.3 dB. Figure 7b shows the configuration recovered through the proposed approach which has an output SINR of 20.96 dB. The proposed approach thus recovers the hybrid sparse array with performance close to the best possible, moreover it approximately yields 3 dB advantage over worst fully augmentable hybrid array. As MRAs are not unique we started with a different 8 element MRA structured array (red elements in Fig. 7c), to further reinforce the effectiveness of fully augmentable sparse arrays. The dynamic performance range associated with MRA of Fig. 7c, is from 17.59 dB to 21.3 dB. The performance in this case is very similar to the aforementioned MRA configuration with the output SINR of 21.08 dB for the hybrid array recovered through proposed methodology (Fig. 7c). The maximum possible SINR offered by both hybrid arrays is 21.3 dB which is extremely close to SINR performance of 21.32 dB offered by the optimum array without augmentability constraint.

1) *Monte Carlo Simulation:* We generate 3500 Monte Carlo simulations for comparison between the performance of the sparse arrays that are designed freely and that of sparse array design involving full augmentability constraint. We choose 16 antennas out of 24 available locations. The desired source DOA is fixed with SNR of 10 dB as in IV-A1. We assume twelve narrowband interferences drawn uniformly from 20° to 160° with respective INRs uniformly distributed from 10 dB

to 15 dB. For binary search, the upper and lower limit of the sparsity parameter μ is 5 and 0.01 respectively and $\epsilon = 0.1$, for all 3500 scenarios. Fig. 8 shows the average SINR performance, where the proposed NFSDR-approach is only 0.57 dB suboptimal relative to the optimum array found through enumeration (choosing 16 antennas out of 24 involves 735471 prospective configurations). However, this performance is achieved by sparse arrays without ensuring the augmentability constraint. Therefore, we prefix 8 antennas in MRA topology, namely Hybrid 1 and Hybrid 2 prefix configurations, shown in red circles in Figs. 7b and Fig. 7c respectively. The MaxSINR performance, found by enumeration, for either of the underlying hybrid topologies competes very closely as evident in Fig. 8. The average MaxSINR (found by enumeration), under both prefixed configurations, is only compromised by 0.28 dB relative to the average MaxSINR performance offered without the augmentability constraint. It is noted that in this case, the possible sparse configurations are drastically reduced from 735471 to 12870 (choose the remaining 8 antennas from the remaining 16 possible locations due to prefixing 8 antennas *a priori*). It is clear from Fig. 8 that the proposed FSDR algorithm successfully recovers the hybrid sparse array with an average SINR performance loss of 0.8 dB. We remark that the performance of the hybrid sparse array is still slightly better than the optimum sparse array receive beamforming proposed in [35] that assumes the knowledge of jammers' steering vectors and utilizes all the available degrees of freedom, unlike the hybrid sparse array.

D. Fully augmentable 2D arrays

Consider a 7×7 planar array with grid pacing of $\lambda/2$ where we place 24 antennas at 49 possible positions. A desired source is impinging from elevation angle $\theta = 50^\circ$ and azimuth angle of $\phi = 90^\circ$. Here, elevation angle is with respect to the plane carrying the array rather than reference from the zenith. Four strong interferes are impinging from $(\theta = 20^\circ, \phi = 30^\circ)$, $(\theta = 40^\circ, \phi = 80^\circ)$, $(\theta = 120^\circ, \phi = 75^\circ)$ and $(\theta = 35^\circ, \phi = 20^\circ)$. The INR corresponding to each interference is 20 dB and SNR is set to 0 dB. There are of the order of 10^{14} possible 24 antenna configurations, hence the problem is prohibitive even by exhaustive search. Therefore, we resort to the upper bound of performance limits to compare our results. Here, we utilize the fact that the best possible performance occurs when the interferes are completely canceled in the array output and the output SINR in that case would equal the array gain offered by the 24 element array which amounts to 13.8 dB. Figure 9 shows the optimum antenna locations recovered by the proposed NFSDR-approach. The output SINR for this configuration is 13.68 dB which is sufficiently close to the ideal performance. It should be noted that again the array recovered in the Fig. 9 is not fully augmentable as it is missing quite a few correlation lags.

We now introduce the condition of full augmentability by placing 19 antennas in nested lattice configuration [55] to form a filled co-array (red elements in Fig. 10). The rest of five available antennas can be placed in the remaining 30 possible locations hence resulting in approximately 1.5×10^5

possibilities. Figure 10 shows the hybrid sparse geometry recovered by FSDR algorithm and offers SINR of 13.25 dB which is around 0.4 dB less than the optimum array. The performance range of the hybrid arrays associated with the structured nested lattice array ranges from 11.4 dB to 13.38 dB (found through exhaustive search). In this regard the FSDR algorithm finds the hybrid sparse array with the performance degradation of little more than 0.1 dB. The worst performing hybrid array (Fig. 11) has an output SINR of 11.4 dB and is around 2 dB lower than the best performing hybrid sparse array.

It is of interest to compare the performance of aforementioned sparse arrays with a compact 2D array. For this purpose, we chose a 6×4 rectangular array. The compact rectangular array performs very poorly in the underlying scenario and has an output SINR of 7.8 dB which is more than 5 dB down from the hybrid sparse array recovered through the semidefinite relaxation. This performance degradation is very clear from the beampattern of both arrays shown in Figs. 12 and 13 (normalized beampattern in dB). In the case of the hybrid sparse array recovered through FSDR (Fig. 10), the target has the maximum gain towards the direction of interest with minimum gain simultaneously towards all unwanted DOAs (Fig. 12). In contrast, it is clear from Fig. 13 that the beampattern of the compact rectangular array could not manage maximum gain towards the direction of interest while effectively rejecting the interfering signals. Although, the 6×5 and 6×6 compact arrays utilize 6 and 12 additional sensors, yet the respective output SINRs of 9.04 dB and 11 dB are considerably suboptimal relative to the proposed solutions. It is noted that adding 18 additional sensors resulting in 7×6 rectangular array has an output SINR of 12.87 dB. Still, the 24 element free-design as well as the hybrid design outperform the compact 42 element rectangular array. However, a 49 element fully populated 7×7 rectangular array has an output SINR of 14.37 dB, which is marginal improvement given the SINR of 24 element designed topologies. The hybrid array also appears to be more robust as it has higher dynamic performance range threshold (11.4 dB). The performance of arbitrarily designed arrays is more prone to deteriorate catastrophically even far worse than that of the compact uniform or rectangular arrays.

We also test the fully augmentable array design for the case of multiple point source scenario described previously (Section IV-B). The hybrid array recovered through proposed methodology is shown in the Fig. 5c (red elements showing the 7 element MRA). The output SINR is 11.566 dB and is sufficiently close to the performance achieved through enumeration.

V. CONCLUSION

This paper considered fully augmentable sparse array configurations for maximizing the beamformer output SINR for general rank desired signal correlation matrices. It proposed a hybrid sparse array design that simultaneously considers co-array and environment-dependent objectives. The proposed array design approach uses a subset of the available antennas to obtain a fully augmentable array while employing the remaining antennas for achieving the highest SINR. It was shown

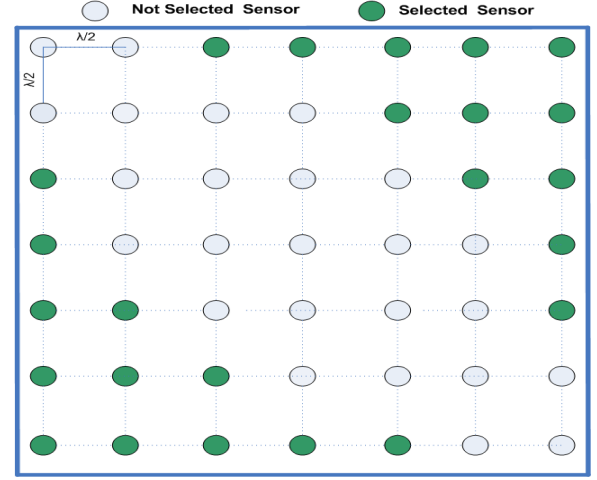


Fig. 9: 24 element antenna sparse array (NFSDR-approach)



Fig. 10: 24 element hybrid antenna sparse array (19 prefixed, 5 selected through FSDR)



Fig. 11: 24 element worst performing hybrid antenna sparse array (19 prefixed, 5 selected)

that the hybrid design is data driven and hence practically viable, as it ensures the availability of the full data correlation

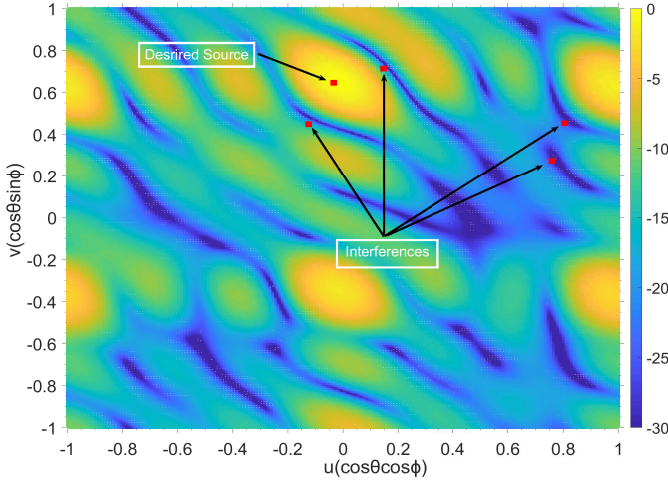


Fig. 12: Beam pattern for the antenna array in Fig. 10

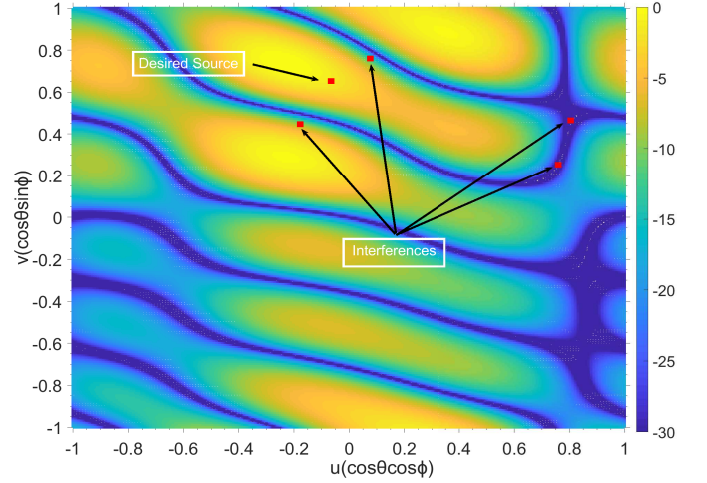


Fig. 13: Beam pattern for a 6×4 compact rectangular array

matrix with a reasonable trade off in the SINR performance. We applied the modified re-weighting QCQP which proved effective in recovering superior SINR performance for hybrid sparse arrays in polynomial run times. The proposed approach was extended for fair gain beamforming towards multiple sources. We solved the optimization problem by both the proposed algorithms and enumeration and showed strong agreement between the two methods.

APPENDIX

PROOF OF THE CONJUGATE SYMMETRIC PROPERTY OF OPTIMAL WEIGHT VECTOR

Proof. The correlation matrix \mathbf{R} for centro-symmetric arrays have a conjugate persymmetric structure such that [56]:

$$\mathbf{T}\mathbf{R}'\mathbf{T} = \mathbf{R} \quad (16)$$

Here $\{\cdot\}$ is the conjugate operator and \mathbf{T} is the transformation matrix which flips the entries of a vector upside down by left multiplication;

$$\mathbf{T} = \begin{bmatrix} 0 & \dots & 0 & 0 & 1 \\ 0 & \dots & 0 & 1 & 0 \\ \vdots & \dots & \vdots & \vdots & \vdots \\ 1 & \dots & 0 & 0 & 0 \end{bmatrix}$$

The optimal weight vector which maximizes the SINR is given by;

$$\mathbf{w}_o = \mathcal{P}\{\mathbf{R}_{s'}^{-1}\mathbf{R}_s\} \quad (17)$$

where,

$$\{\mathbf{R}_{s'}^{-1}\mathbf{R}_s\}\mathbf{w}_o = \Lambda_{max}\mathbf{w}_o \quad (18)$$

Using the relation in (16), (18) can be re-expressed as follows,

$$\begin{aligned} \{(\mathbf{T}\mathbf{R}_{s'}'\mathbf{T})^{-1}(\mathbf{T}\mathbf{R}_s'\mathbf{T})\}\mathbf{w}_o &= \Lambda_{max}\mathbf{w}_o \\ \{\mathbf{T}^{-1}(\mathbf{R}_{s'}')^{-1}\mathbf{T}^{-1}(\mathbf{T}\mathbf{R}_s'\mathbf{T})\}\mathbf{w}_o &= \Lambda_{max}\mathbf{w}_o \end{aligned} \quad (19)$$

Multiplying both sides by \mathbf{T} and applying the conjugate operator,

$$\{\mathbf{R}_{s'}^{-1}\mathbf{R}_s\}\mathbf{T}\mathbf{w}_o' = \Lambda_{max}\mathbf{T}\mathbf{w}_o' \quad (20)$$

From (20), we note, that $\mathbf{T}\mathbf{w}_o'$ is also the principal eigenvector associated with matrix $\mathbf{R}_{s'}^{-1}\mathbf{R}_s$. Since the principal eigenvector of the positive definite hermitian matrix is unique up to the scalar complex multiplier, this directly implies that;

$$\mathbf{w}_o = \mathbf{T}\mathbf{w}_o'$$

■

REFERENCES

- [1] S. A. Hamza and M. G. Amin, "Hybrid sparse array design for under-determined models," in *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2019, pp. 4180–4184.
- [2] S. A. Hamza, M. G. Amin, and G. Fabrizio, "Optimum sparse array beamforming for general rank signal models," in *2018 IEEE Radar Conference (RadarConf18)*, April 2018, pp. 1343–1347.
- [3] G. R. Lockwood, J. R. Talman, and S. S. Brunke, "Real-time 3-D ultrasound imaging using sparse synthetic aperture beamforming," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 45, no. 4, pp. 980–988, July 1998.
- [4] O. Mehanna, N. D. Sidiropoulos, and G. B. Giannakis, "Joint multicast beamforming and antenna selection," *IEEE Transactions on Signal Processing*, vol. 61, no. 10, pp. 2660–2674, May 2013.
- [5] Y. He and K. P. Chong, "Sensor scheduling for target tracking in sensor networks," in *2004 43rd IEEE Conference on Decision and Control (CDC) (IEEE Cat. No.04CH37601)*, vol. 1, Dec 2004, pp. 743–748 Vol.1.
- [6] W. V. Cappellen, S. J. Wijnholds, and J. D. Bregman, "Sparse antenna array configurations in large aperture synthesis radio telescopes," in *2006 European Radar Conference*, Sept 2006, pp. 76–79.
- [7] S. Joshi and S. Boyd, "Sensor selection via convex optimization," *IEEE Transactions on Signal Processing*, vol. 57, no. 2, pp. 451–462, Feb 2009.
- [8] H. Godrich, A. P. Petropulu, and H. V. Poor, "Sensor selection in distributed multiple-radar architectures for localization: A knapsack problem formulation," *IEEE Transactions on Signal Processing*, vol. 60, no. 1, pp. 247–260, Jan 2012.
- [9] S. P. Chepuri and G. Leus, "Sparsity-promoting sensor selection for non-linear measurement models," *IEEE Transactions on Signal Processing*, vol. 63, no. 3, pp. 684–698, Feb 2015.
- [10] A. Moffet, "Minimum-redundancy linear arrays," *IEEE Transactions on Antennas and Propagation*, vol. 16, no. 2, pp. 172–175, March 1968.
- [11] 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, Aug. 2010.
- [12] S. Qin, Y. D. Zhang, and M. G. Amin, "Generalized coprime array configurations for direction-of-arrival estimation," *IEEE Transactions on Signal Processing*, vol. 63, no. 6, pp. 1377–1390, March 2015.

- [13] E. BouDaher, Y. Jia, F. Ahmad, and M. G. Amin, "Multi-frequency co-prime arrays for high-resolution direction-of-arrival estimation," *IEEE Transactions on Signal Processing*, vol. 63, no. 14, pp. 3797–3808, July 2015.
- [14] H. Unz, "Linear arrays with arbitrarily distributed elements," *IRE Transactions on Antennas and Propagation*, vol. 8, no. 2, pp. 222–223, March 1960.
- [15] R. Harrington, "Sidelobe reduction by nonuniform element spacing," *IRE Transactions on Antennas and Propagation*, vol. 9, no. 2, pp. 187–192, March 1961.
- [16] A. Maffett, "Array factors with nonuniform spacing parameter," *IRE Transactions on Antennas and Propagation*, vol. 10, no. 2, pp. 131–136, March 1962.
- [17] Y. T. Lo and S. W. Lee, "A study of space-tapered arrays," 1966.
- [18] P. Jarske, T. Saramaki, S. K. Mitra, and Y. Neuvo, "On properties and design of nonuniformly spaced linear arrays (antennas)," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 36, no. 3, pp. 372–380, March 1988.
- [19] R. M. Leahy and B. D. Jeffs, "On the design of maximally sparse beamforming arrays," *IEEE Transactions on Antennas and Propagation*, vol. 39, no. 8, pp. 1178–1187, Aug 1991.
- [20] W. Roberts, L. Xu, J. Li, and P. Stoica, "Sparse antenna array design for MIMO active sensing applications," *IEEE Transactions on Antennas and Propagation*, vol. 59, no. 3, pp. 846–858, March 2011.
- [21] D. Caratelli and M. C. Vigan, "Analytical synthesis technique for linear uniform-amplitude sparse arrays," *Radio Science*, vol. 46, no. 4, 2011.
- [22] R. L. Haupt, "Thinned arrays using genetic algorithms," *IEEE Transactions on Antennas and Propagation*, vol. 42, no. 7, pp. 993–999, July 1994.
- [23] A. Trucco and V. Murino, "Stochastic optimization of linear sparse arrays," *IEEE Journal of Oceanic Engineering*, vol. 24, no. 3, pp. 291–299, July 1999.
- [24] B. Fuchs, "Application of convex relaxation to array synthesis problems," *IEEE Transactions on Antennas and Propagation*, vol. 62, no. 2, pp. 634–640, Feb. 2014.
- [25] S. Eng Nai, W. Ser, Z. Liang Yu, and H. Chen, "Beampattern synthesis for linear and planar arrays with antenna selection by convex optimization," vol. 58, pp. 3923 – 3930, 01 2011.
- [26] G. Prisco and M. D'Urso, "Maximally sparse arrays via sequential convex optimizations," *IEEE Antennas and Wireless Propagation Letters*, vol. 11, pp. 192–195, 2012.
- [27] M. B. Hawes and W. Liu, "Sparse array design for wideband beamforming with reduced complexity in tapped delay-lines," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 22, no. 8, pp. 1236–1247, Aug 2014.
- [28] A. Goldsmith, *Wireless Communications*. New York, NY, USA: Cambridge University Press, 2005.
- [29] H. L. V. Trees, *Detection, Estimation, and Modulation Theory: Radar-Sonar Signal Processing and Gaussian Signals in Noise*. Melbourne, FL, USA: Krieger Publishing Co., Inc., 1992.
- [30] J. Li, P. Stoica, and Z. Wang, "On robust Capon beamforming and diagonal loading," *IEEE Transactions on Signal Processing*, vol. 51, no. 7, pp. 1702–1715, July 2003.
- [31] X. Wang, E. Aboutanios, M. Trinkle, and M. G. Amin, "Reconfigurable adaptive array beamforming by antenna selection," *IEEE Transactions on Signal Processing*, vol. 62, no. 9, pp. 2385–2396, May 2014.
- [32] N. D. Sidiropoulos, T. N. Davidson, and Z.-Q. Luo, "Transmit beamforming for physical-layer multicasting," *IEEE Transactions on Signal Processing*, vol. 54, no. 6, pp. 2239–2251, June 2006.
- [33] V. Roy, S. P. Chepuri, and G. Leus, "Sparsity-enforcing sensor selection for DOA estimation," in *2013 5th IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*, Dec. 2013, pp. 340–343.
- [34] X. Wang, M. Amin, and X. Cao, "Analysis and design of optimum sparse array configurations for adaptive beamforming," *IEEE Transactions on Signal Processing*, vol. PP, no. 99, pp. 1–1, 2017.
- [35] X. Wang and M. Amin, "Design of optimum sparse array for robust MVDR beamforming against DOA mismatch," in *2017 IEEE 7th International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*, Dec 2017, pp. 1–5.
- [36] X. Wang, M. G. Amin, X. Wang, and X. Cao, "Sparse array quiescent beamformer design combining adaptive and deterministic constraints," *IEEE Transactions on Antennas and Propagation*, vol. PP, no. 99, pp. 1–1, 2017.
- [37] Y. I. Abramovich, D. A. Gray, A. Y. Gorokhov, and N. K. Spencer, "Positive-definite Toeplitz completion in DOA estimation for nonuniform linear antenna arrays. I. Fully augmentable arrays," *IEEE Transactions on Signal Processing*, vol. 46, no. 9, pp. 2458–2471, Sep 1998.
- [38] Y. Abramovich, N. Spencer, and A. Gorokhov, "Positive-definite Toeplitz completion in DOA estimation for nonuniform linear antenna arrays. II. Partially augmentable arrays," *Trans. Sig. Proc.*, vol. 47, no. 6, pp. 1502–1521, Jun. 1999.
- [39] A. Bertrand and M. Moonen, "Efficient sensor subset selection and link failure response for linear MMSE signal estimation in wireless sensor networks," in *2010 18th European Signal Processing Conference*, Aug 2010, pp. 1092–1096.
- [40] J. Szurley, A. Bertrand, M. Moonen, P. Ruckebusch, and I. Moerman, "Energy aware greedy subset selection for speech enhancement in wireless acoustic sensor networks," in *2012 Proceedings of the 20th European Signal Processing Conference (EUSIPCO)*, Aug 2012, pp. 789–793.
- [41] J. Zhang, S. P. Chepuri, R. C. Hendriks, and R. Heusdens, "Microphone subset selection for MVDR beamformer based noise reduction," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 26, no. 3, pp. 550–563, March 2018.
- [42] S. Shahbazpanahi, A. B. Gershman, Z.-Q. Luo, and K. M. Wong, "Robust adaptive beamforming for general-rank signal models," *IEEE Transactions on Signal Processing*, vol. 51, no. 9, pp. 2257–2269, Sept. 2003.
- [43] P. Stoica and R. L. Moses, *Introduction to spectral analysis*. Upper Saddle River, N.J. : Prentice Hall, 1997.
- [44] R. B. Ertel, P. Cardieri, K. W. Sowerby, T. S. Rappaport, and J. H. Reed, "Overview of spatial channel models for antenna array communication systems," *IEEE Personal Communications*, vol. 5, no. 1, pp. 10–22, Feb. 1998.
- [45] D. L. Donoho, "For most large underdetermined systems of linear equations the minimal l_1 -norm solution is also the sparsest solution," *Communications on Pure and Applied Mathematics*, vol. 59, no. 6, pp. 797–829.
- [46] A. M. Bruckstein, D. L. Donoho, and M. Elad, "From sparse solutions of systems of equations to sparse modeling of signals and images," *SIAM Rev.*, vol. 51, no. 1, pp. 34–81, Feb. 2009. [Online]. Available: <http://dx.doi.org/10.1137/060657704>
- [47] A. Y. Yang, S. S. Sastry, A. Ganesh, and Y. Ma, "Fast l_1 -minimization algorithms and an application in robust face recognition: A review," in *2010 IEEE International Conference on Image Processing*, Sep. 2010, pp. 1849–1852.
- [48] H. L. Taylor, S. C. Banks, and J. F. McCoy, "Deconvolution with the l_1 norm," *GEOPHYSICS*, vol. 44, no. 1, pp. 39–52, 1979. [Online]. Available: <https://doi.org/10.1190/1.1440921>
- [49] E. J. Candès, M. B. Wakin, and S. P. Boyd, "Enhancing sparsity by reweighted l_1 minimization," *Journal of Fourier Analysis and Applications*, vol. 14, no. 5, pp. 877–905, Dec. 2008.
- [50] M. Bengtsson and B. Ottersten, "Optimal downlink beamforming using semidefinite optimization," 1999.
- [51] Z. q. Luo, W. k. Ma, A. M. c. S. Y. Ye, and S. Zhang, "Semidefinite relaxation of quadratic optimization problems," *IEEE Signal Processing Magazine*, vol. 27, no. 3, pp. 20–34, May 2010.
- [52] B. Recht, M. Fazel, and P. A. Parrilo, "Guaranteed minimum-rank solutions of linear matrix equations via nuclear norm minimization," *SIAM Rev.*, vol. 52, no. 3, pp. 471–501, Aug. 2010.
- [53] K. Mohan and M. Fazel, "Iterative reweighted algorithms for matrix rank minimization," *J. Mach. Learn. Res.*, vol. 13, no. 1, pp. 3441–3473, Nov. 2012.
- [54] R. Rajamki and V. Koivunen, "Symmetric sparse linear array for active imaging," in *2018 IEEE 10th Sensor Array and Multichannel Signal Processing Workshop (SAM)*, July 2018, pp. 46–50.
- [55] P. Pal and P. P. Vaidyanathan, "Nested arrays in two dimensions, Part 1: Geometrical considerations," *IEEE Transactions on Signal Processing*, vol. 60, no. 9, pp. 4694–4705, Sept 2012.
- [56] K.-C. Huang and C.-C. Teh, "Adaptive beamforming with conjugate symmetric weights," *IEEE Transactions on Antennas and Propagation*, vol. 39, no. 7, pp. 926–932, July 1991.