Parametric Dictionary Learning for TWRI Using Distributed Particle Swarm Optimization

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***Abstract*—This paper considers a distributed network of through-the-wall radars for accurate indoor scene reconstruction in the presence of multipath propagation. A sparsity based method is proposed for eliminating ghost targets under imperfect knowledge of interior wall locations. Instead of aggregating and processing the observations at a central fusion station, joint scene reconstruction and estimation of interior wall locations is carried out in a distributed manner across the network. More specifically, an alternating minimization approach is utilized to solve the associated non-convex optimization problem, wherein the sparse scene is reconstructed using the recently proposed modified distributed orthogonal matching pursuit algorithm while the wall location estimates are obtained with a novel distributed particle swarm optimization algorithm (D-PSO) proposed in this paper. Existing literature on averaging consensus is leveraged to derive the D-PSO algorithm. The efficacy of proposed approach is demonstrated using numerical simulation.**

I. Introduction

With significant advances in through-the-wall radar imaging (TWRI) technology over the last decade, one of the remaining challenges is dealing effectively with the high amount of multipath in indoor environments [1], [2]. A variety of multipath exploitation approaches, both under conventional and sparse reconstruction frameworks, have been recently proposed in the literature [3]–[10]. However, these methods require prior exact knowledge of the interior layout of the building being interrogated to eliminate ghost targets (accumulation of unwanted energy at incorrect target locations) and provide enhanced image quality. In practice, this information may not be available in advance.

Inaccuracies in knowledge of the interior building layout and the room geometry can lead to severe impairments in the effectiveness of multipath exploitation approaches. In [11], a TWRI radar network comprising several man-portable units, deployed in either a co-located or distributed configuration, were considered. A multipath signal model, with the unknown wall locations as parameters, was developed and employed to jointly perform sparsity-based image reconstruction and wall location estimation. An alternating minimization approach was used to solve the joint optimization problem, wherein group sparse reconstruction was employed for scene recovery and Particle Swarm Optimization (PSO) algorithm [12], [13] was shown to work well for determining the wall locations. For the distributed setting, the method proposed in [11] required that the measurements be first aggregated at a centralized location. For a large number of radar units, transmitting data to a central processing center may not be feasible. In such settings, a method that can learn wall locations and localize the targets without aggregating all the data at a centralized location is highly desirable.

In this paper, we consider a distributed configuration of multiple radar units to image stationary indoor scenes in the presence of wall location inaccuracies. The use of a distributed radar network is emerging as an effective and flexible alternative to single-site radar systems in TWRI applications. We focus on solving the joint optimization problem for estimation of wall locations and sparse image reconstruction via alternating minimization in a distributed manner, without requiring a central processing station. For the scene recovery step, we employ a distributed variant of the Orthogonal Matching Pursuit (OMP) algorithm, called MDOMP, which was recently proposed in [14].

In order to solve the optimization problem for estimation of wall locations in distributed settings, we employ consensus averaging [15] to develop a distributed variant of the PSO algorithm. There have been previous attempts at developing distributed versions of PSO [16]–[19]. A master-slave architecture is employed in [16]; each node is responsible for computing the objective function for a subset of particles, which are then aggregated at the master node to update the particles. A peer-to-peer algorithm for PSO is proposed in [17], where each node is capable of computing the objective function locally and is responsible for updating a subset of particles. However, all of the aforementioned PSO variants are not distributed in the true sense, since they require centralized control to operate. Further, these algorithms assume each node to be capable of computing the objective function at any particle value. The proposed algorithm eliminates these shortcomings of the aforementioned methods.

The paper is organized as follows. In Section II, the signal model and the problem formulation are presented for the distributed radar network. The alternating minimization based approach is discussed in Section III, where the proposed distributed variant of the PSO is described in detail. Supporting simulation results are provided in Section IV, while conclusions are drawn in Section V.

II. Problem Formulation

A. Signal Model

Consider S radar units, distributed at known positions either along the front wall or surrounding the building being interrogated. Each radar unit is equipped with M transmitters and N receivers, where both M and N are assumed to be small. An 'across-units' mode of operation is considered, wherein transmission-reception occurs across multiple radar units. That is, each transmitted pulse is received simultaneously by all receivers from all units. It is assumed that the individual radar units can transmit and receive without interference from others and each radar can associate the received signal with a specific transmitter. These objectives can be achieved either by using orthogonal waveforms or through sequential use of the transmitters. In the latter case, the transmitted signals become orthogonal by virtue of time-multiplexing. In this paper, we assume that the transmitter-receiver association is accomplished by activating the transmitters sequentially.

Let s_1 and s_2 be the indices of the transmitting and receiving radar units, respectively, where $s_1 = 0, 1, \ldots, S-1$, and $s_2 = 0, 1, \ldots, S-1$. The scene of interest is divided into P grid points, which define the target space. Because of the deployment of the radar units in a distributed fashion, the target radar cross section (RCS) changes across the units. Let $\sigma_p^{s_1 s_2}$ be the complex reflectivity associated with grid point p corresponding to the transmitting unit s_1 and receiving unit s_2, with $\sigma_p^{s_1 s_2} = 0$ representing the absence of a target. Neglecting multipath contributions, the baseband signal recorded at receiver $n = 0, 1, \ldots, N-1$ of the s_2th radar unit, with transmitter $m = 0, 1, \ldots, M-1$ of the s_1th radar unit active, can be expressed as,

$$z_{mn}^{s_1 s_2}(t) = \sum_{p=0}^{P-1} \sigma_p^{s_1 s_2} s(t - mT_r - s_1 MT_r - \tau_{pmn}^{s_1 s_2}) \times \exp\left(-j2\pi f_c (mT_r + s_1 MT_r + \tau_{pmn}^{s_1 s_2})\right). \tag{1}$$

Here, $s(t)$ is the transmitted wideband pulse in complex baseband, f_c is the carrier frequency, T_r is the pulse repetition interval, and $\tau_{pmn}^{s_1 s_2}$ is the propagation delay from transmitter m of unit s_1 to the grid point p and back to the receiver n of unit s_2. We sample $z_{mn}^{s_1 s_2}(t)$ at or above the Nyquist rate to obtain a signal vector $\mathbf{z}_{mn}^{s_1 s_2}$ of length N_T. Stacking signal vectors corresponding to the M transmitters and N receivers, we obtain the $MNN_T \times 1$ measurement vector $\bar{\mathbf{z}}_{s_1 s_2}$, which, using (1), can be expressed as

$$\bar{\mathbf{z}}_{s_1 s_2} = \mathbf{\Psi}_{s_1 s_2}^{(0)} \boldsymbol{\sigma}_{s_1 s_2}^{(0)}, \tag{2}$$

where $\boldsymbol{\sigma}_{s_1 s_2}^{(0)} = [\sigma_0^{s_1 s_2}, \sigma_1^{s_1 s_2}, \ldots, \sigma_{P-1}^{s_1 s_2}]^{\mathsf{T}}$, the superscript '(0)' indicates direct path propagation, '$[.]^{\mathsf{T}}$' denotes matrix transpose, and, for $i = 0, \ldots, N_T - 1$, the elements of the dictionary matrix $\mathbf{\Psi}_{s_1 s_2}^{(0)} \in \mathbb{C}^{MNN_T \times P}$ are given by,

$$\begin{aligned} &\left[\mathbf{\Psi}_{s_1 s_2}^{(0)}\right]_{i+nN_T+mN_T N, p} = \\ &s(t_i - mT_r - s_1 MT_r - \tau_{pmn}^{s_1 s_2}) \times \\ &\exp\left(-j2\pi f_c (t_i - (mT_r + s_1 MT_r + \tau_{pmn}^{s_1 s_2}))\right). \end{aligned} \tag{3}$$

We assume that the target multipath is generated due to secondary reflections at one or more interior walls. Parameterizing the interior wall locations as $\mathbf{w} \in \mathbb{R}^3$ and employing geometric optics to model $R-1$ additive multipath contributions in the received signal, we obtain the signal model under multipath propagation for the s_1th transmitting unit and s_2th receiving unit as

$$\bar{\mathbf{z}}_{s_1 s_2} = \mathbf{\Psi}_{s_1 s_2}^{(0)} \boldsymbol{\sigma}_{s_1 s_2}^{(0)} + \sum_{r=1}^{R-1} \mathbf{\Psi}_{s_1 s_2}^{(r)}(\mathbf{w}) \boldsymbol{\sigma}_{s_1 s_2}^{(r)}, \tag{4}$$

where $\mathbf{\Psi}_{s_1 s_2}^{(r)}$ is defined according to (3) with $\tau_{pmn}^{s_1 s_2}$ replaced by the propoagation delay $\tau_{pmn}^{s_1 s_2,(r)}$ between transmitter m, grid point p, and receiver n along the rth multipath [7]. Note that the change in the target RCS across the $R-1$ multipath signals is captured in the model by $\boldsymbol{\sigma}_{s_1 s2}^{(r)}$, which is the target reflectivity vector corresponding to the rth multipath. Further, note that the multipath time delays $\tau_{mnp}^{s_1 s_2,(r)}, r = 1, \ldots, R-1$, depend on the wall locations and, therefore, the dictionary matrices $\{\mathbf{\Psi}_{s_1 s_2}^{(r)}\}_{r=1}^{R-1}$ are all functions of $\mathbf{w}$. Defining $\widetilde{\mathbf{\Psi}}_{s_1 s_2}(\mathbf{w}) = \left[\mathbf{\Psi}_{s_1 s_2}^{(0)} \mathbf{\Psi}_{s_1 s_2}^{(1)}(\mathbf{w}) \cdots \mathbf{\Psi}_{s_1 s_2}^{(R-1)}(\mathbf{w})\right]$ and $\widetilde{\boldsymbol{\sigma}}_{s_1 s_2} = [\boldsymbol{\sigma}_{s_1 s_2}^{(0)^{\mathsf{T}}} \boldsymbol{\sigma}_{s_1 s_2}^{(1)^{\mathsf{T}}} \cdots \boldsymbol{\sigma}_{s_1 s_2}^{(R-1)^{\mathsf{T}}}]^{\mathsf{T}}$, we can rewrite the signal model in (4) as

$$\bar{\mathbf{z}}_{s_1 s_2} = \widetilde{\mathbf{\Psi}}_{s_1 s_2}(\mathbf{w}) \widetilde{\boldsymbol{\sigma}}_{s_1 s_2} + \bar{\mathbf{n}}_{s_1 s_2}. \tag{5}$$

Here, $\bar{\mathbf{n}}$ denotes the system noise vector.

B. Centralized Problem Formulation

In case of centralized processing, the S^2 measurement vectors, $\{\bar{\mathbf{z}}_{s_1 s_2}, s_1 = 0, \ldots, S-1, s_2 = 0, \ldots, S-1\}$, corresponding to the 'across-units' operation of the S radar units, are communicated to a fusion center where the scene reconstruction is performed. Under distributed deployment, the radar units are widely separated and the targets' aspect angles may vary considerably across the units. As such, a coherent combination of the various measurements is not feasible. Therefore, the S^2 measurements can be collectively represented as

$$\breve{\mathbf{z}} = \breve{\mathbf{A}}(\mathbf{w}) \breve{\boldsymbol{\sigma}} + \breve{\mathbf{n}}. \tag{6}$$

where

$$\begin{aligned} \breve{\mathbf{z}} &= \left[\bar{\mathbf{z}}_{0\,0}^{\mathsf{T}}, \bar{\mathbf{z}}_{0\,1}^{\mathsf{T}}, \ldots, \bar{\mathbf{z}}_{S-1\,S-1}^{\mathsf{T}}\right]^{\mathsf{T}}, \\ \breve{\boldsymbol{\sigma}} &= \left[\widetilde{\boldsymbol{\sigma}}_{0\,0}^{\mathsf{T}}, \widetilde{\boldsymbol{\sigma}}_{0\,1}^{\mathsf{T}}, \ldots, \widetilde{\boldsymbol{\sigma}}_{S-1\,S-1}^{\mathsf{T}}\right]^{\mathsf{T}}, \\ \breve{\mathbf{n}} &= \left[\bar{\mathbf{n}}_{0\,0}^{\mathsf{T}}, \bar{\mathbf{n}}_{0\,1}^{\mathsf{T}}, \ldots, \bar{\mathbf{n}}_{S-1\,S-1}^{\mathsf{T}}\right]^{\mathsf{T}}, \text{ and} \\ \breve{\mathbf{A}}(\mathbf{w}) &= \text{blkdiag}\{\widetilde{\mathbf{\Psi}}_{0\,0}(\mathbf{w}), \widetilde{\mathbf{\Psi}}_{0\,1}(\mathbf{w}), \ldots, \widetilde{\mathbf{\Psi}}_{S-1\,S-1}(\mathbf{w})\}. \end{aligned} \tag{7}$$

Given the measurements $\breve{\mathbf{z}}$ in (6), the aim is to determine the wall locations $\mathbf{w}$ as well as reconstruct the scene reflectivity vector $\breve{\boldsymbol{\sigma}}$. Since the same physical scene is observed via all paths by the various radar units, the scene reflectivity vector exhibits a group sparse structure [11]. As such, the scene recovery and wall location estimation can be posed as the following optimization problem:

$$\min_{\breve{\boldsymbol{\sigma}}, \mathbf{w}} \|\breve{\mathbf{z}} - \breve{\mathbf{A}}(\mathbf{w}) \breve{\boldsymbol{\sigma}}\|_2^2 + \lambda \|\breve{\boldsymbol{\sigma}}\|_{1,2}, \tag{8}$$

where

$$\|\breve{\boldsymbol{\sigma}}\|_{1,2} = \sum_{p=0}^{P-1} \big\| [\boldsymbol{\sigma}^{(0)}_{0\,0_p}, \ldots, \boldsymbol{\sigma}^{(R-1)}_{0\,0_p}, \ldots, \boldsymbol{\sigma}^{(0)}_{S-1\,S-1_p}, \ldots, \boldsymbol{\sigma}^{(R-1)}_{S-1\,S-1_p}]^{\mathsf{T}} \big\|_2. \quad (9)$$

The optimization problem in (8) is non-convex as the matrix $\breve{\mathbf{A}}(\mathbf{w})$ has a nonlinear dependence on the wall locations. An iterative approach is proposed in [11], which solves (8) by alternating between optimization over $\breve{\boldsymbol{\sigma}}$ and $\mathbf{w}$.

C. Distributed Problem Formulation

The focus of this work is on wall location estimation and scene reconstruction, i.e., solving (8), in a distributed manner across the S radar units, with each radar unit having access to only a subset of the measurements $\breve{\mathbf{z}}$. Substituting $\breve{\mathbf{A}}(\mathbf{w})$, $\breve{\mathbf{z}}$, and $\breve{\boldsymbol{\sigma}}$ from (7) in (8), we can express the optimization problem as

$$\min_{\breve{\boldsymbol{\sigma}},\mathbf{w}} \sum_{s_2=0}^{S-1} \sum_{s_1=0}^{S-1} \|\bar{\mathbf{z}}_{s_1\,s_2} - \tilde{\boldsymbol{\Psi}}_{s_1\,s_2}(\mathbf{w})\widetilde{\boldsymbol{\sigma}}_{s_1\,s_2}\|_2^2 + \lambda\|\breve{\boldsymbol{\sigma}}\|_{1,2}. \quad (10)$$

Under the alternating minimization framework, the objective function in (10) for a fixed $\mathbf{w}$ is convex in $\breve{\boldsymbol{\sigma}}$. A variety of sparsity based methods exist for determining $\breve{\boldsymbol{\sigma}}$ in a decentralized setting [14], [20]–[23]. On the other hand, for a fixed $\breve{\boldsymbol{\sigma}}$, the objective function is just the first term in (10). That is,

$$\min_{\mathbf{w}} \sum_{s_2=0}^{S-1} \left[\sum_{s_1=0}^{S-1} \|\bar{\mathbf{z}}_{s_1\,s_2} - \tilde{\boldsymbol{\Psi}}_{s_1\,s_2}(\mathbf{w})\widetilde{\boldsymbol{\sigma}}_{s_1\,s_2}\|_2^2 \right]. \quad (11)$$

Clearly, the expression in the brackets in (11) is the objective function at radar unit s_2, and as such, it permits solution of the optimization problem in a distributed manner.

III. Proposed approach

We solve (10) by alternating minimization over variables $\mathbf{w}$ and $\breve{\boldsymbol{\sigma}}$. Since the measurements are available at spatially distributed sites, we need to employ a method that solves for both $\mathbf{w}$ and $\breve{\boldsymbol{\sigma}}$ in distributed settings. For distributed optimization over $\breve{\boldsymbol{\sigma}}$, we use Modified Distributed OMP (MDOMP) method proposed in [14]. For the non-convex optimization problem with respect to $\mathbf{w}$, we develop a distributed variant of the PSO algorithm. In the following, we first provide an overview of the working of the conventional PSO algorithm, followed by a brief review of consensus averaging, which is utilized to develop the distributed version of PSO. Then, we present the proposed distributed PSO (D-PSO) algorithm and briefly describe MDOMP.

A. Overview of Particle Swarm Optimization

In order to optimize an objective function $f(\mathbf{x})$, PSO is initialized with Q particles at positions $\{\mathbf{q}_j\}_{j=1}^{Q}$, which are points in the domain of $f(\mathbf{x})$. We define the variable $\mathbf{q}_{\min,j}$, which contains the value of $\mathbf{q}_j$ corresponding to the obtained minimum value of the objective function thus far for the particle j. In each iteration of PSO, we compute the value of the objective function for each particle $\{\mathbf{q}_j\}_{j=1}^{Q}$ and update the variables $\{\mathbf{q}_{\min,j}\}_{j=1}^{Q}$. Then we update the variable $\mathbf{g}_{\min}$, which is the particle value at which we have observed the minimum value of objective function so far. That is,

$$\mathbf{g}_{\min} = \arg \min_{\mathbf{q}\in\{q_j\}_{j=1}^{Q}} f(\mathbf{q}).$$

Finally, we update the particle velocity $\mathbf{v}_j$ and particle value $\mathbf{q}_j$, where the velocity $\mathbf{v}_j$ provides the displacement of the particle $\mathbf{q}_j$ in the domain of objective function $f(\mathbf{x})$. The velocity update is based on the particle's current value $\mathbf{q}_j$, minimum value at the particle $\mathbf{q}_{\min,j}$, and the minimum value across all particles $\mathbf{g}_{\min}$. The velocity update equation for centralized PSO is the same as for distributed PSO, which is given in Step 20 of Algorithm 1.

B. Consensus Averaging

For some scalar values $\{x_i\}_{i=0}^{S-1}$ that are distributed across S radar units, consensus averaging provides an iterative method for computing the average $(1/S)\sum_{i=0}^{S-1} x_i$. Connectivity among these distributed radar units can be represented by a graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, where $\mathcal{N} = \{0, 1, \ldots, S-1\}$ is the set of nodes (radar units in the underlying application) in a network and $\mathcal{E}$ are the edges defining the interconnection among the nodes i.e., $(i,i) \in \mathcal{E}$ and $(i,j) \in \mathcal{E}$ when node i can communicate with node j. From graph $\mathcal{G}$, we generate a doubly stochastic matrix $\mathbf{W}$ such that its (i,j)th entry, $\mathbf{W}_{i,j}$, satisfies the condition

$$\mathbf{W}_{i,j} = \begin{cases} > 0 & , (i,j) \in \mathcal{E}, \\ 0 & , (i,j) \notin \mathcal{E}. \end{cases}$$

We initialize consensus averaging by $\mathbf{x}^{(0)} = [x_0, \ldots, x_{S-1}]$ and the update at iteration t_c of consensus averaging is given by,

$$\mathbf{x}^{(t_c)} = \mathbf{W}\mathbf{x}^{(t_c-1)}. \quad (12)$$

Previous work on consensus averaging [15], [24] shows that if $\mathbf{W}$ is doubly stochastic then as $t_c \to \infty$, each element of $\mathbf{x}^{(t_c)}$ approaches the mean of the values in $\mathbf{x}^{(0)}$.

C. Distributed Particle Swarm Optimization

We develop a distributed variant of the PSO algorithm (D-PSO), whose pseudocode is provided in Algorithm 1. Similar to the conventional PSO, we start by initializing with Q particles $\{\mathbf{q}^{(0)}_{s_2,j}\}_{j=1}^{Q}$ at the s_2th node/radar unit. We assume that each radar unit has the same initial values for the particles[1]. The first step towards updating the value of a particle consists of computing the objective function (10) at the current value of the particle. In the distributed case, each radar unit can only compute a part of the objective function, as specified in Step 3 of Algorithm 1. Using consensus averaging, we compute the complete value of the objective function, as delineated in Steps 4–8 of Algorithm 1. Next, in Steps 9–12, we update the minimum objective value achieved by the

[1]One way of achieving this is by initializing particles randomly with the same seed at each node.

Algorithm 1: Distributed Particle Swarm Optimization algorithm (D-PSO).

Input: Local data $\{\bar{\mathbf{z}}_{0\,0}, \ldots, \bar{\mathbf{z}}_{S-1\,S-1}\}$, $\breve{\sigma_i}$ computed using MDOMP, and doubly-stochastic matrix $\mathbf{W}$.
Initialize: Generate particles with positions $\{\mathbf{q}^{(0)}_{s_2,j}\}_{j=1}^{Q}$ and velocities $\{\mathbf{v}^{(0)}_{s_2,j}\}_{j=1}^{Q}$ randomly at each site s_2.
$h_{min,j,s_2} \leftarrow \infty$, $b_{min,s_2} \leftarrow \infty$. $t \leftarrow 0$.

1: **while** $stopping\ rule$ **do**
2:   **for** $j = 1, \ldots, Q$ **do**
3:     Calculate at each radar unit s_2:
$h_{s_2} \leftarrow \sum_{s_1=0}^{S-1} \|\bar{\mathbf{z}}_{s_1\,s_2} - \tilde{\mathbf{\Psi}}_{s_1\,s_2}(\mathbf{q}^{(t)}_{s_2,j})\widetilde{\boldsymbol{\sigma}}_{s_1\,s_2}\|_2^2$
4:     ***(Inititalize Consensus Averaging)*** Set $t_c \leftarrow 0$ and $\widehat{h}^{(0)} \leftarrow \left[h_0 \ldots h_{S-1}\right]^{\mathsf{T}}$
5:     **while** $stopping\ rule$ **do**
6:       $\widehat{h}^{(t_c)}_{s_2} \leftarrow \sum_{j \in \mathcal{N}_{s_2}} \mathbf{W}_{s_2,j} \widehat{h}^{(t_c-1)}_{j}$
7:       $t_c \leftarrow t_c + 1$
8:     **end while**
9:     **if** $\widehat{h}_{s_2} < h_{min,j,s_2}$ **then**
10:       $h_{min,j,s_2} \leftarrow \widehat{h}_{s_2}$
11:       $\mathbf{q}_{min,j,s_2} \leftarrow \mathbf{q}^{(t)}_{s_2,j}$
12:     **end if**
13:   **end for**
14:   $k_{s_2} \leftarrow \arg\min_j \{h_{min,j,s_2}\}$
15:   **if** $h_{min,k_{s_2},s_2} < b_{min,s_2}$ **then**
16:     $b_{min,s_2} \leftarrow h_{min,k_{s_2},s_2}$
17:     $\mathbf{g}_{min,s_2} \leftarrow \{\mathbf{q}_{min,k_{s_2},s_2}\}$
18:   **end if**
19:   **for** $j = 1, \ldots, Q$ **do**
20:     Update velocity:
$\mathbf{v}^{(t+1)}_{s_2,j} \leftarrow \mathbf{v}^{(t)}_{s_2,j} + c_1\mathcal{U}(0,1)(\mathbf{q}_{\min,j,s_2} - \mathbf{q}^{(t)}_{i,j}) + c_2\mathcal{U}(0,1)(\mathbf{g}_{\min} - \mathbf{q}^{(t)}_{s_2,j})$
21:     Update positions: $\mathbf{q}^{(t)}_{s_2,j} \leftarrow \mathbf{q}^{(t)}_{s_2,j} + \mathbf{v}^{(t)}_{s_2,j}$.
22:   **end for**
23:   $t \leftarrow t + 1$
24: **end while**
Return: $\{\mathbf{q}^{(t)}_{s_2,j}\}_{j=1}^{Q}$.

particle $\mathbf{q}_{s_2,j}$. We repeat Steps 3–12 for all Q particles at the radar unit s_2. The velocity $\mathbf{v}_{s_2,j}$ and particle values $\mathbf{q}_{s_2,j}$ are updated as detailed in Steps 20–21 of Algorithm 1. Note that in Step 20, $\mathcal{U}(0,1)$ is a random number chosen from a uniform distribution over the interval $[0,1]$.

D. MDOMP for Distributed Sparse Scene Recovery

MDOMP has been proposed in [14] for sparse scene recovery in case of a distributed network of through-the-wall radar units. MDOMP is a distributed version of the OMP algorithm [25]. At every radar unit, a communication step is performed in each iteration, wherein the unit shares its correlation vector, obtained using the local measurements only, with all other radar units. Each unit then adds all correlation vectors, selects the index corresponding to the largest element in the correlation vector sum, and updates its set of indices. The remaining part of the algorithm is similar to OMP.

IV. Simulation Results

For simulations, we consider a square room with four walls, each of length 4 m. We deploy $S = 3$ and $S = 5$ radar units, uniformly distributed over an extent of 2 m in crossrange, at a standoff distance of 3 m from the front wall. Each radar unit is equipped with $M = 1$ transmitter and $N = 3$ receivers. As already explained in Section II-A, we use time-multiplexing, i.e., at any given time instant, only one radar unit transmits and all units receive the reflections. For each transmission, we use a Gaussian pulse with 50% relative bandwidth, modulating a sinusoid of carrier frequency $f_c = 2$ GHz. The received signal at each radar unit is sampled at the Nyquist rate and $N_T = 150$ samples are collected over the interval of interest. In addition to the direct signal, we assume two multipath contributions arising from the side walls, i.e., $R = 3$. Multipath returns are assumed to be attenuated by 6 dB as compared to the direct path signal. Further, the received signals are assumed to be corrupted by complex circular Gaussian noise, resulting in a signal-to-noise ratio (SNR) of 20 dB.

The region of interest covers the room interior and is divided into 64×64 pixels in crossrange and downrange. We perform 35 Monte Carlo trials for each configuration, i.e., $S = 3$ and $S = 5$ radar units. Four point targets are assumed to be located within the room at distinct locations; the crossrange and downrange coordinates of the target locations are varied from one trial to the next. In each trial, we randomly select the initial position estimate of the left wall from the interval $[-2.5, -1.5]$ m, while that for the right wall is chosen from the interval $[1.5, 2.5]$ m. Table I lists the mean values and the variances of the location estimates of the two side walls obtained using the proposed D-PSO algorithm. We can see that for both cases i.e., $S = 3$ and $S = 5$, we obtain comparable estimates of the wall locations. The reconstructed scene for one of the trials corresponding to the $S = 5$ radar units configuration is depicted in Fig. 1.

Further, we evaluate the performance of the D-PSO algorithm in terms of the detection rate. We define detection rate as the ratio of the number of targets detected correctly to the total number of targets present in the scene. Again, for each case, we perform 35 Monte Carlo trials. For the case of $S = 3$ radar units, D-PSO achieved, on average, a detection rate of 91.87%, whereas the detection rate for the $S = 5$ radar units configuration was determined to be 91.43%. This demonstrates that the performance of the D-PSO algorithm does not change significantly with variations in the number of radar units employed.

V. Conclusion

In this paper, we have proposed a distributed variant of the particle swarm optimization algorithm for wall position estimation in an alternating minimization approach to sparsity-based multipath exploitation. Sparse through-the-wall scene reconstruction is carried out using the MDOMP algorithm. The proposed approach permits learning of wall locations and localizing the indoor targets in a distributed fashion across a radar network without the need for a centralized processing center. Simulation results are provided which validate the performance of the proposed scheme.

TABLE I

x-COORDINATES OF THE TRUE WALL LOCATIONS AND THE ESTIMATED VALUES USING D-PSO FOR $S = 3$ AND $S = 5$ RADAR UNITS.

	Wall Location	Mean Estimated Location ($S = 3$)	Variance ($S = 3$)	Mean Estimated Location ($S = 5$)	Variance ($S = 5$)
Left wall	-2	-1.9902	0.0018	-1.987	0.0025
Right wall	2	2.0005	0.0039	2	0.0055

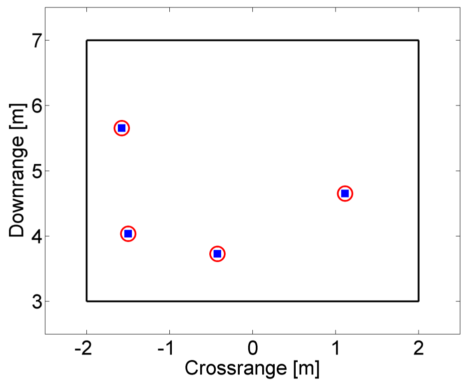

Fig. 1. Scene reconstruction using D-PSO and MDOMP algorithms.The true target locations are indicated by red circles.

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