Distributed Greedy Sparse Recovery for Through-the-Wall Radar Imaging

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Abstract — A modified distributed orthogonal matching pursuit algorithm is presented for sparse scene reconstruction in through-the-wall radar imaging applications. A distributed network of radar systems, each equipped with a single transmitter and an array of receivers, is considered. Ray-tracing based numerical simulation results are provided which demonstrate the effectiveness of the proposed algorithm.

Index Terms – Compressive Sensing, Distributed Radar, Through-the-Wall, Greedy Algorithms.

I. INTRODUCTION

Through-the-wall radar imaging (TWRI) provides the ability to "see" through walls by means of electromagnetic waves [1]. This emerging technology is highly desirable in applications, such as search and rescue missions, surveillance and reconnaissance. Compressive Sensing (CS) has been successfully applied to TWRI for reducing the acquired data volume, typically associated with high-resolution imaging [2]. However, most of the CS work has focused on either single-site radar deployment [2], or a distributed network of radars with a centralized processing station [3].

In this paper, we consider a distributed network of TWRI systems wherein the sparse recovery is carried out in a distributed manner across the various systems. Such a configuration provides a fail-safe solution for TWRI since the image reconstruction is neither tied to a single array nor any centralized data fusion is required.

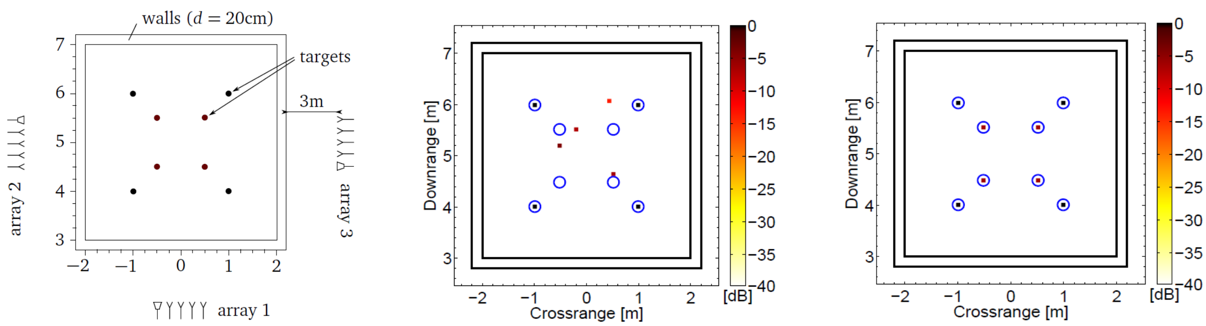
Greedy signal recovery algorithms, such as orthogonal matching pursuit (OMP), have been recently modified so that the reconstruction is performed at distributed sensors [4]. This paper proposes an enhancement of Distributed OMP (DOMP) to improve the reconstruction accuracy. Numerical results based on ray-tracing are provided, which demonstrate the superiority of the proposed Modified DOMP over DOMP.

II. DISTRIBUTED SPARSE RECOVERY

Given L distributed arrays, with the measurement vector and dictionary of the lth array denoted by $\mathbf{y}_l$ and $\mathbf{A}_l$, respectively, distributed OMP is executed at each array to recover the corresponding image $\mathbf{x}_l$ with a specified sparsity level S. The pseudocode for DOMP is as follows:

1. $i = 1$, $\mathbf{U}_{l,0}$ (support set) = $\varnothing$, $\mathbf{r}_{l,0}$ (residual) = $\mathbf{y}_l$
2. Compute observation vector $\mathbf{c}_{l,i} = |\mathbf{A}_l^H \mathbf{r}_{l,i-1}|$
3. Locate index $\tilde{\mathbf{U}}_{l,i}$ of the largest entry of $\mathbf{c}_{l,i}$
4. Communicate $\tilde{\mathbf{U}}_{l,i}$ to the other arrays and receive their $\tilde{\mathbf{U}}_{k,i}, k \neq l, k = 1,\ldots,L$
5. Select index λ_i with highest frequency of occurrence from $\tilde{\mathbf{U}}_{l,i}, \forall l$
6. $\tilde{\mathbf{U}}_{l,i} = \tilde{\mathbf{U}}_{l,i-1} \cup \lambda_i$ and compute $\mathbf{r}_{l,i}$ (calculated as in the standard OMP)
7. Increment i and go to step 2 if $i \leq S$.
8. Set $\mathbf{U}_l = \tilde{\mathbf{U}}_{l,i}$. Obtain $\mathbf{x}_l = (\breve{\mathbf{A}}_l^H \breve{\mathbf{A}}_l)^{-1} \breve{\mathbf{A}}_l^H \mathbf{y}_l$, where $\breve{\mathbf{A}}_l$ contains only the columns of $\mathbf{A}_l$ corresponding to the set $\mathbf{U}_l$.

Finally, the images $\mathbf{x}_l$, $l = 1,\ldots, L$ are merged to yield a composite image $\mathbf{x}$ by computing the ℓ_2-norm over each element separately. Note that in



(a) (b) (c)

Fig. 1. (a) Scene Layout; (b) DOMP based reconstruction; (c) MDOMP based reconstruction.

step 5 of DOMP, if no single index with highest frequency of occurrence can be identified, then λ_i is randomly selected at each array from amongst $\tilde{\mathbf{U}}_{l,i}, \forall l$ [4]. As such, it is possible that different arrays are choosing different indices and, hence, the set $\mathbf{U}_l$ may not be the same for all arrays.

We propose a modification to DOMP, wherein steps 3-5 are replaced by the following procedure. The arrays communicate their respective observation vectors $\mathbf{c}_{l,i}$ (computed in step 2) to each other. Then, each array determines the index of maximum value of $\sum_{l=1}^{L} \mathbf{c}_{l,i}$ and assigns it to λ_i. This results in a tie-breaking and ensures that the same indices are selected in all arrays. The remaining steps of the Modified DOMP (MDOMP) are the same as in DOMP.

III. NUMERICAL RESULTS

We simulate a scene containing eight point targets inside a room, and three arrays, each consisting of one transmitter and four receivers, distributed around the room, as shown in Fig. 1(a). The standoff distance of each array from the corresponding wall is 3 m and the inter-element spacing is set to 10 cm. A random phase, uniformly distributed between 0 and 2π, is attributed to target returns for each array, simulating the different viewpoints of the arrays. The reflectivity of the inner four targets is assumed to be one-half the reflectivity of the outer four targets. The walls are 20 cm thick with relative permittivity of 7.66. A modulated Gaussian pulse with 1 GHz bandwidth centered at 2 GHz is transmitted sequentially from each array and the received signals are sampled at the Nyquist rate to obtain the measurement vectors $\mathbf{y}_l$. White Gaussian noise is added to the received signals with a signal-to-noise ratio of 20 dB.

The sparsity level is set to eight for both DOMP and MDOMP and the corresponding results are provided in Figs. 1(b) and (c), respectively. From Fig. 1(b), we observe that DOMP recovered the four outer targets exactly, but failed to estimate the support of the four inner targets, leading to four falsely reconstructed targets, which are only from 5 to 10 dB lower in intensity than the true targets. On the other hand, MDOMP reconstructs all eight targets perfectly, as depicted in Fig. 1(c).

IV. CONCLUSION

In this paper, we have proposed a modification of the distributed OMP algorithm for sparse recovery of through-the-wall images using a distributed network of radar systems. Reconstruction results based on ray-tracing data demonstrated the superior performance of the proposed modification over the existing method.

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