

MULTIPATH EXPLOITATION IN SPARSE SCENE RECOVERY USING SENSING-THROUGH-WALL DISTRIBUTED RADAR SENSOR CONFIGURATIONS

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ABSTRACT

In this paper, we consider multipath exploitation and sparse reconstruction in a network of distributed multistatic radar units for stationary target localization behind walls. Multipath exploitation leverages prior information of the indoor scattering environment to eliminate ghost targets. However, uncertainties in interior wall positions severely impair the effectiveness of multipath exploitation. We develop a multipath signal model for the distributed radar network configuration, which parameterizes the wall locations, and perform joint optimization for simultaneously recovering the target and wall positions. Supporting simulation results are provided, which validate the effectiveness of the proposed method.

Index Terms— Multipath exploitation, distributed radar network, sparse reconstruction, target localization

1. INTRODUCTION

With much progress made in through-the-wall radar imaging (TWRI) over the last decade, one of the remaining challenges is dealing effectively with the rich multipath indoor environment [1, 2]. Signal propagation not only occurs along the direct path between the antenna and the target, but also along various indirect paths involving secondary reflections at interior building walls, floor, and ceiling. Such multipath returns can result in ghost targets or energy accumulation at locations that do not correspond to true targets in the scene. Different properties of direct and indirect radar returns can be used to identify and suppress the indirect returns [3, 4]. Alternatively, the energy contained in the multipath returns can be utilized for enhanced target detection and localization, while simultaneously eliminating the ghost targets. The latter is the underlying principle of multipath exploitation [5–8].

Multipath exploitation, in general, requires prior information of the indoor scattering environment. Inaccuracies in the

knowledge of interior building layout and the room geometry can lead to severe impairments in the effectiveness of the multipath exploitation schemes. In ground-based operations, these impairments depend on the employed antenna aperture as well as whether RF sensing is performed using co-located or distributed system configurations. In this paper, we consider a distributed network of multistatic radar units for stationary target localization. Sequential operation of the transmitters from all the radar units is assumed and each transmitted pulse is received simultaneously by all receivers from all radar units. The data from all transmit and receive pairs are transmitted to a central processing unit, where the acquired measurements are non-coherently combined due to varying target radar cross section (RCS) across the units. We develop a parameterized multipath propagation model with the positions of the walls represented as parameters and solve a joint optimization problem to simultaneously perform a ghost-free sparse scene recovery and wall location estimation at the central processing unit.

Multipath exploitation in the presence of wall uncertainties was first proposed for TWRI in [9]. However, a co-located configuration of multiple transmitters and receivers was assumed therein, thereby permitting the radar returns corresponding to all the transmitters and receivers to be coherently combined for each propagation path. For ground-based operations, deployment of a network of multistatic radar units, each with a limited number of transmitters and receivers, can provide an effective and agile alternative to vehicle-mounted systems. In such cases, it is more appealing to define distributed configurations since it may be difficult to deploy precise co-located configurations.

The remainder of the paper is organized as follows. In Section 2, we establish the received signal model for the distributed network of multistatic radars in a multipath environment. Section 3 describes the optimization problem for multipath exploitation in the presence of wall uncertainties. Supporting simulation results are provided in Section 4. Section 5 concludes the paper.

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2. SIGNAL MODEL

2.1. Single Multistatic Radar Unit

Consider a wideband multistatic coherent radar with M transmitters and N receivers. Sequential use of the M transmitters with simultaneous reception at all N receivers is assumed. Let the 2-D target space be discretized into a grid of P points, with $\mathbf{x}_p = (x_p, y_p)$ and σ_p denoting the position and complex reflectivity of the p th grid point. A zero value of σ_p represents the absence of a point target at the p th grid point. For a sparse scene, only few of the grid points assume non-zero values.

Let the transmitted wideband pulse be expressed as $\Re\{s(t)\exp(j2\pi f_c t)\}$, where $s(t)$ is the pulse in the complex baseband, and f_c is the carrier frequency. The sequential operation of the transmitters results in a temporal spacing of T_r between the pulses. Let \mathbf{z}_{mn} be the $N_T \times 1$ vector obtained by sampling the direct radar return, corresponding to the (m, n) th transmitter-receiver pair, at N_T time steps with sampling interval T_s . Stacking the direct return vectors $\{\mathbf{z}_{mn}, m = 0, \dots, M-1, n = 0, \dots, N-1\}$, we obtain the $MNN_T \times 1$ vector

$$\mathbf{z} = \Psi^{(0)} \boldsymbol{\sigma}^{(0)}, \quad (1)$$

where $\boldsymbol{\sigma}^{(0)}$ is the $P \times 1$ vector of target reflectivities corresponding to the direct path and $\Psi^{(0)}$ is the $MNN_T \times P$ direct path dictionary matrix, defined as

$$\begin{aligned} [\Psi^{(0)}]_{i+nN_T+mN_TN,p} = \\ s(t_i - mT_r - \tau_{pmn}) \cdot \exp(-j2\pi f_c(mT_r + \tau_{pmn})), \end{aligned} \quad (2)$$

Here, τ_{pmn} is the bistatic propagation delay from the m th transmitter to the p th target and back to the n th receiver, $i = 0, \dots, N_T - 1$, $m = 0, \dots, M - 1$, $n = 0, \dots, N - 1$, and $p = 0, \dots, P - 1$.

Modeling $R - 1$ additive multipath contributions in the received signal, we obtain

$$\mathbf{z} = \Psi^{(0)} \boldsymbol{\sigma}^{(0)} + \Psi^{(1)}(w_1) \boldsymbol{\sigma}^{(1)} + \dots + \Psi^{(R-1)}(w_{R-1}) \boldsymbol{\sigma}^{(R-1)},$$

where $\Psi^{(r)}(w_r)$, $r = 1, \dots, R - 1$ are the dictionaries under multipath propagation, w_r are the wall locations and $\boldsymbol{\sigma}^{(r)}$ are the reflectivity vectors for each path.

Finally, we concatenate the dictionaries as $\tilde{\Psi}(\mathbf{w}) = [\Psi^{(0)} \ \Psi^{(1)}(w_1) \ \dots \ \Psi^{(R-1)}(w_{R-1})] \in \mathbb{C}^{N_T N K \times PR}$ and stack the image vectors corresponding to the various paths in a $PR \times 1$ vector $\tilde{\boldsymbol{\sigma}} = [(\boldsymbol{\sigma}^{(0)})^T (\boldsymbol{\sigma}^{(1)})^T \dots (\boldsymbol{\sigma}^{(R-1)})^T]^T$, obtaining

$$\mathbf{z} = \tilde{\Psi}(\mathbf{w}) \tilde{\boldsymbol{\sigma}} + \tilde{\mathbf{n}}, \quad (3)$$

where \mathbf{w} is the vector of all wall positions.

Note that the front wall contributions are assumed to have been removed by a suitable wall clutter removal method [10–13] and are, thus, not included in the signal model.

2.2. Distributed Network Model

Assume that a number S of the multistatic radar units described above are distributed around the scene of interest. Each transmitted pulse is received simultaneously by all receivers from all units. Hence, the total number of measurements is increased S^2 -fold. We denote the measurement vectors as $\{\tilde{\mathbf{z}}_{s^{\text{Tx}} s^{\text{Rx}}}, s^{\text{Tx}}, s^{\text{Rx}} = 0, \dots, S - 1\}$, where s^{Tx} and s^{Rx} are the indexes of the transmitting and receiving units, respectively. Likewise, the dictionaries $\tilde{\Psi}_{s^{\text{Tx}} s^{\text{Rx}}}(\mathbf{w})$ depend on the transmitting and receiving units, whereas the wall position vector \mathbf{w} is universal. An additive noise vector \mathbf{n} for the full received signal is considered. In order to account for the RCS change that is inherent in a distributed configuration, a separate reflectivity vector $\tilde{\boldsymbol{\sigma}}_{s^{\text{Tx}} s^{\text{Rx}}}$ for each combination of s^{Tx} and s^{Rx} is introduced. Therefore, we obtain the signal model for the distributed network of S multistatic radars as

$$\tilde{\mathbf{z}} = \tilde{\Psi}(\mathbf{w}) \tilde{\boldsymbol{\sigma}} + \mathbf{n}, \quad (4)$$

where

$$\tilde{\mathbf{z}} = \begin{bmatrix} \tilde{z}_{0 \ 0} \\ \tilde{z}_{0 \ 1} \\ \vdots \\ \tilde{z}_{0 \ S-1} \\ \vdots \\ \tilde{z}_{S-1 \ S-1} \end{bmatrix}, \quad \tilde{\boldsymbol{\sigma}} = \begin{bmatrix} \tilde{\sigma}_{0 \ 0} \\ \tilde{\sigma}_{0 \ 1} \\ \vdots \\ \tilde{\sigma}_{0 \ S-1} \\ \vdots \\ \tilde{\sigma}_{S-1 \ S-1} \end{bmatrix}, \quad (5)$$

$$\tilde{\Psi}(\mathbf{w}) = \text{blkdiag} \begin{pmatrix} \tilde{\Psi}_{0 \ 0}(\mathbf{w}) \\ \tilde{\Psi}_{0 \ 1}(\mathbf{w}) \\ \vdots \\ \tilde{\Psi}_{0 \ S-1}(\mathbf{w}) \\ \vdots \\ \tilde{\Psi}_{S-1 \ S-1}(\mathbf{w}) \end{pmatrix} \quad (6)$$

and $\text{blkdiag}(\cdot)$ denotes the block diagonal matrix operation.

3. SPARSE SCENE RECONSTRUCTION UNDER WALL UNCERTAINTIES

In practice, precise prior knowledge of the interior wall locations \mathbf{w} is usually not available. The walls locations rather have to be estimated from the returns using building layout estimation techniques, such as [13–15]. These estimates are subject to errors that will certainly be on the order of TWRI system wavelengths. Multipath exploitation requires accurate knowledge of the room layout in order to deliver high quality reconstructions. Wall location errors lead to a mismatch between the signal model and the received signal, resulting in performance degradation [9]. As such, it is imperative to take wall position uncertainties into account during the reconstruction process.

To this end, we propose a joint scheme for reconstruction of the target space and estimation of the wall positions. As the same target scene is observed via all propagation paths and by all distributed radar units, the reflectivity vector $\check{\sigma}$ exhibits a group sparse structure. As such, the joint scene reconstruction and wall parameter estimation problem can be posed as the mixed-norm nested optimization problem

$$\min_w \min_{\check{\sigma}} \|\check{z} - \check{\Psi}(w)\check{\sigma}\|_2^2 + \lambda \|\check{\sigma}\|_{1,2}. \quad (7)$$

where $\|\cdot\|_{1,2}$ denotes mixed ℓ_1 - ℓ_2 norm and λ is a regularization parameter. The mixed norm optimization problem, which results due to the group sparse nature of $\check{\sigma}$, can be solved in an iterative fashion. The group encompasses one location across all paths and all distributed radar units. We note that the inner optimization over $\check{\sigma}$ is a convex optimization problem, which can be solved by using SparSA [16] or other available schemes [17, 18]. The outer minimization is non-convex. However, the dimension of the solution space is much smaller and, thus, easier to search. In a typical scenario, the number of unknown wall locations is two to four, whereas the number of image pixels is several orders of magnitude larger. Non-derivative Quasi-Newton methods, Genetic Algorithm based methods [19], or Particle Swarm Optimization (PSO) [20] can be used to solve the outer minimization. In order to improve the convergence for such methods, the search space should be limited to a feasible region. We assume that we have initial estimates of the wall locations, which are within a 0.5 m error margin. These initial estimates are assumed to have been obtained by a prior surveillance operation for building layout determination. The error margin of 0.5 m is chosen in accordance with the VisiBuilding Program by the DARPA [21]. Hence, the search space is limited by box constraints centered around each initial wall location estimate.

4. SIMULATION RESULTS

Simulations were performed for a simple rectangular room enclosed by four homogeneous walls. The size of the room is 4 m by 4 m, i.e. the walls are located 2 m away from the center of the room. The walls are modeled with thickness $d = 20$ cm and relative permittivity $\epsilon_r = 7.66$, which is typical of concrete. Access to the outside perimeter of the room from the front and back sides is assumed. Two multistatic radar units are located at 3 m standoff distance on opposing sides of the room, as shown in Fig. 1. Each of the $S = 2$ multistatic radar units has a uniform linear array with $N = 3$ receivers and an inter-element spacing of 10 cm. The central element also acts as a transmitter, i.e., $M = 1$. When one unit is transmitting, both units simultaneously record the returns with all of their receivers. All measurements are finally assumed to be available at a single data processing center where the scene recovery is carried out.

Each unit is oriented parallel to the wall facing it and transmits modulated Gaussian pulses, centered around $f_c =$

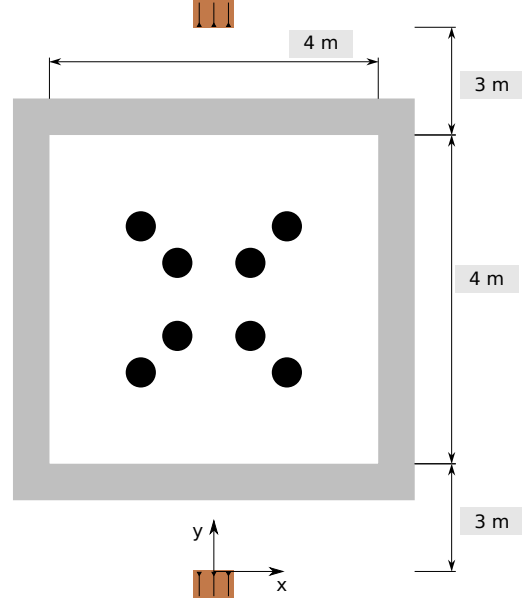


Fig. 1. Scene geometry.

2 GHz, with a relative bandwidth of 50%. At each receiver, $T = 150$ fast time samples are collected in the relevant interval, covering the target and multipath returns with a sampling rate of $f_s = 4$ GHz. For each array, each side wall is assumed to cause 3 different multipath returns. Multipath associated with the back and front walls is not considered. For each side wall, we observe two different first order multipath returns. A first order multipath involves only one reflection at an interior wall, which could take place either on the way from the transmitter to the target or from the target back to the receiver. Also, we consider one second-order multipath for each wall, where a secondary reflections takes place on both ways. In total, there are $R = 7$ paths that are considered in the received signal corresponding to each transmit-receive pair. The multipath returns are all considered to be 6 dB weaker than the direct path.

We also consider additive complex circular Gaussian noise. We consider two scenarios, one with perfect wall position estimates and the other with errors in the estimates of the side wall locations. Errors in positions of the front and back walls are not considered in this example, since the multipath returns are assumed to be due to secondary reflections at the side walls only. The target space extends 5 m each in crossrange and downrange and is centered at the center of the room. The target space is spatially discretized into $P = 64 \times 64$ grid points. Eight targets of equal reflectivity are considered at specific locations in the room, as illustrated in Fig. 1.

We first performed scene reconstruction assuming perfect knowledge of the wall positions. That is, we only solved the inner optimization problem in (7) once with the true wall po-

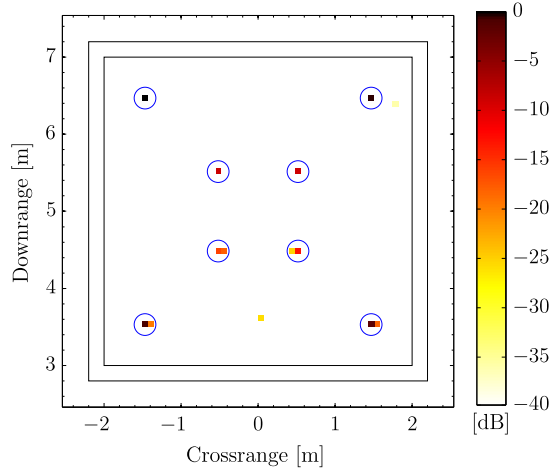


Fig. 2. Benchmark - No wall errors.

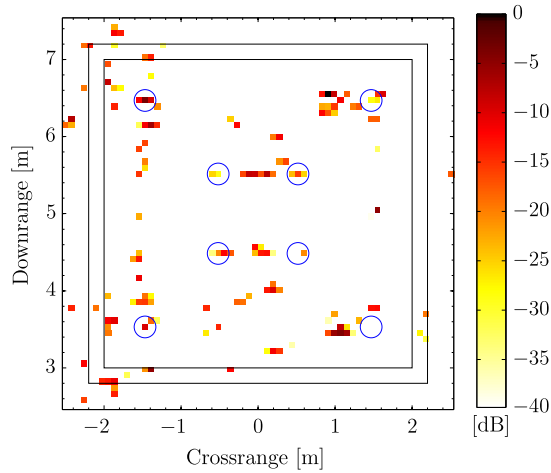


Fig. 3. Sparse Reconstruction with wall errors.

sitions used for the w vector. This benchmark reconstruction result is shown in Fig. 2. The current and subsequent reconstruction results are all shown on a 40 dB scale. We observe that the scene is reconstructed almost perfectly when prior knowledge of the exact wall locations is available. However, if the initial wall location estimates are set to 1.6 m and -1.7 m with respect to the y-axis of the coordinate system, scene reconstruction fails completely, as shown in Fig. 3. This highlights the need for the proposed wall correction method. Next, we used a particle swarm optimization toolbox for Matlab [20] to solve the proposed nested optimization problem. The resulting reconstruction is provided in Fig. 4. It is evident that the proposed approach is able to vastly improve the reconstruction quality over Fig. 3, with the result being on par with the known wall location or benchmark case. The estimated wall positions are 1.999 m and -2.003 m, with the estimation error in the millimeter range.

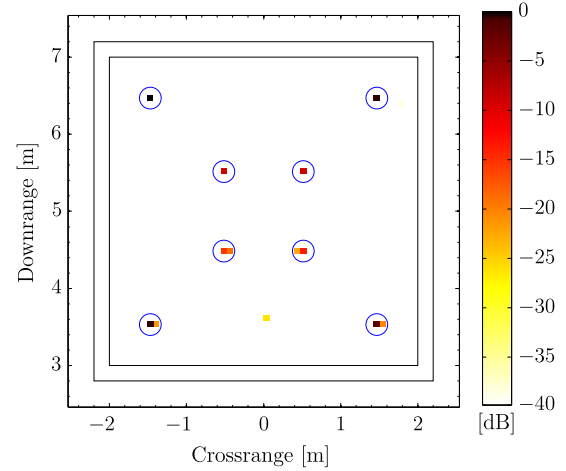


Fig. 4. Sparse Reconstruction with PSO based wall position estimates.

5. CONCLUSION

In this paper, we presented a joint sparse scene reconstruction and wall location estimation approach for multipath exploitation in a distributed network of multistatic radars for through-the-wall radar sensing applications. A network of distributed multistatic radar unit provides more flexibility and ease of deployment over both co-located configurations and vehicle-borne TWRI systems. By introducing a parametrized model of the scattering environment, uncertainties in the interior wall locations were captured in the signal model. The resulting joint optimization problem is convex in the unknown target reflectivities, but non-convex in the wall parameters, and can be solved in an iterative manner. Supporting simulation results were provided, which validated the performance of the proposed nested optimization approach for target localization using a distributed radar network.

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