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6. AUTHORS

Fauzia Ahmad, Moeness G. Amin

7. PERFORMING ORGANIZATION NAMES AND ADDRESSES

Villanova University
800 Lancaster Avenue
Tolentine 121
Villanova, PA 19085 -1603

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14. ABSTRACT

This report presents the results of the research performed under Contract W911NF-11-1-0536 over the period of October 1, 2011 to September 30, 2016. The research team working on this project consisted of Dr. Fauzia Ahmad (Principal Investigator, currently with Temple University), Dr. Moeness Amin (Co-Principal Investigator), Dr. Davide Comite (Post-Doctoral Research Fellow), and Mr. Khodour AlKadry (Graduate Assistant).

The primary objective of this effort is to develop appropriate signal models and algorithms for behind-the-wall

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Final Report: Multipath Exploitation & Knowledge Based Urban Radar Imaging Using Compressive Sensing

ABSTRACT

This report presents the results of the research performed under Contract W911NF-11-1-0536 over the period of October 1, 2011 to September 30, 2016. The research team working on this project consisted of Dr. Fauzia Ahmad (Principal Investigator, currently with Temple University), Dr. Moeness Amin (Co-Principal Investigator), Dr. Davide Comite (Post-Doctoral Research Fellow), and Mr. Khodour AlKadry (Graduate Assistant).

The primary objective of this effort is to develop appropriate signal models and algorithms for behind-the-wall stationary and moving target localization and building layout mapping within the CS framework. A secondary objective is to enable enhanced imaging and detection of low-signature buried targets in forward-looking ground penetrating radar applications. To this end, we have made the following main contributions: 1) Mitigation of clutter and stationary targets through conversion of populated scenes to sparse scenes based on Moving Target Indication techniques; 2) Effective front wall clutter suppression under reduced data volume for detection of stationary targets behind walls; 3) Exploitation of the rich multipath nature of the indoor environment in conjunction with compressive sensing for improved stationary target detection and localization in sparse scene scenarios; 4) Enhanced detection and tracking of moving targets through multipath exploitation; 5) Utilization of prior information of building construction practices for determining the building layout under compressive sensing; 6) Robust multipath exploitation based target localization approaches through dictionary learning in the presence of inaccuracies in knowledge of building layout; 7) Effective reconstruction of target scene using a distributed network of through-the-wall radar units in the presence of multipath; 8) Exploitation of target spatial extent for high-resolution through-the-wall radar imaging under the sparse reconstruction framework; 9) Multi-view target detection schemes for forward-looking ground penetrating radar operating at close-to-grazing angles; and 10) Coherence factor based rough surface clutter suppression in forward-looking ground penetrating radar applications.

The research efforts have resulted in a total of 37 publications. These include 14 journal articles that have been published, one journal article that is under review, and 22 conference papers.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Received		Paper
12/24/2016	33	Michael Leigsnering, Fauzia Ahmad, Moeness Amin, and Adelhek Zoubir. Parametric Dictionary Learning for Sparsity-Based TWRI in Multipath Environments, IEEE TRANSACTIONS ON Aerospace and Electronic systems, (11 2014): 532. doi:
12/24/2016	49	Maximillian Stiefel, Michael Leigsnering, Abdelhek Zoubir, Fauzia Ahmad, Moeness Amin. Distributed Greedy Signal Recovery for Through-the-Wall Radar Imaging, IEEE Geoscience and Remote Sensing Letters, ( ): 1477. doi:
TOTAL:		**2**

Number of Papers published in peer-reviewed journals:

(b) Papers published in non-peer-reviewed journals (N/A for none)

Received	Paper

TOTAL:

Number of Papers published in non peer-reviewed journals:

(c) Presentations

Number of Presentations: 0.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
12/24/2016	25	Fauzia Ahmad, Khodour Al Kadry, Moeness G. Amin. Sparsity-based ranging for dual-frequency radars, SPIE Sensing Technology + Applications. 05-MAY-14, Baltimore, Maryland, USA. : ,
12/24/2016	14	Eva Lagunas, Moeness Amin, Fauzia Ahmad, Montse Najar. Improved interior wall detection using designated dictionaries in compressive urban sensing problems, SPIE Compressive Sensing II Conference. 02-MAY-13, Baltimore, MD, USA. : ,
12/24/2016	19	Srdjan Stankovic, Irena Orovic, Moeness Amin. Compressive sensing for sparse time-frequency representation of nonstationary signals in the presence of impulsive noise, SPIE Defense, Security, and Sensing, Compressive Sensing II Conference. 29-APR-13, Baltimore, Maryland, USA. : ,
12/24/2016	50	Davide Comite└, Fauzia Ahmad, Traian Dogaru, Moeness G. Amin. Coherence Factor for Rough Surface Clutter Mitigation in Forward-Looking GPR, IEEE Radar Conference. 08-MAY-17, Seattle, Washington, USA. : ,

TOTAL: **4**

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
12/24/2016	20.00	Fauzia Ahmad, Moeness Amin, Traian Dogaru. A beamforming approach to imaging of stationary indoor scenes under known building layout, 2013 IEEE 5th International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP). 15-DEC-13, St. Martin, France. : ,
12/24/2016	22.00	Michael Leigsnering, Fauzia Ahmad, Moeness Amin, Abdelhak Zoubir. SPECULAR MULTIPATH EXPLOITATION FOR IMPROVED VELOCITY ESTIMATION INTHROUGH-THE-WALL RADAR IMAGING, IEEE International Conference on Acoustics, Speech, and Signal Processing. 04-MAY-14, Florence, Italy. : ,
12/24/2016	31.00	Branka Jokanovic, Moeness G. Amin, Traian Dogaru. Interpolation and sparse reconstructions of Doppler and microDoppler signatures under missing samples, 2014 IEEE Radar Conference (RadarCon). 19-MAY-14, Cincinnati, OH, USA. : ,
12/24/2016	4.00	Fauzia Ahmad, Moeness Amin. Partially sparse reconstruction of behind-the-wall scenes, Compressive Sensing. 27-APR-12, Baltimore, Maryland, USA. : ,
12/24/2016	12.00	Michael Leigsnering, Fauzia Ahmad, Moeness Amin, Abdelhak Zoubir. CS Based Wall Ringing and ReverberationMitigation for Through-the-Wall Radar Imaging, IEEE Radar Conference. 29-APR-13, Ottawa, Canada. : ,
12/24/2016	13.00	Michael Leigsnering, Fauzia Ahmad, Moeness Aminy , Abdelhak Zoubir. Compressive Sensing Based Specular Multipath Exploitation for Through-the-Wall Radar Imaging, IEEE Intternational Conf. on Acoustics, Speech, and Signal Processing. 26-MAY-13, Vancouver, Canada. : ,
12/24/2016	17.00	Fauzia Ahmad, Jiang Qian, Moeness Amin. Wall Mitigation Using Discrete Prolate Spheroidal Sequences for Sparse Indoor Image Reconstruction, 21st European Signal Processign Conference. 09-SEP-13, Marrakech, Morocco. : ,
12/24/2016	18.00	Moeness Amin, Branka Jokanovic, Srdjan Stankovic. Instantaneous frequency and time-frequency signature estimation using compressive sensing, SPIE Defense, Security, and Sensing, Radar Sensor Technology XVII Conference . 29-APR-13, Baltimore, Maryland, USA. : ,
12/24/2016	34.00	Michael Leigsnering , Fauzia Ahmad, Moeness G. Amin, Abdelhak M. Zoubir. Multipath-Aware Velocity Estimation for Sparsity-Based Through-the-Wall Radar Imaging, IEEE International Radar Conference. 11-MAY-15, Arlington, VA, USA. : ,
12/24/2016	35.00	Eva Lagunas, Moeness G. Amin, Fauzia Ahmad. Through-the-Wall Radar Imaging for Heterogeneous Walls using Compressive Sensing, 3rd International Workshop on Compressed Sensing Theoryand its Applications to Radar, Sonar and Remote Sensing. 16-JUN-15, Pisa, Italy. : ,
12/24/2016	37.00	Michael Leigsnering, Fauzia Ahmad, Moeness G. Amin, Abdelhak M. Zoubir. Sparsity-Aware Multipath Exploitation under Wall Position Uncertainties with a Distributed Through-the-Wall Radar Network, IEEE International Conference on Acoustics, Speech, and Signal Processing. 20-APR-15, Gold Coast, Australia,. : ,

12/24/2016 39.00 Khodour Al Kadry, Fauzia Ahmad, Moeness Amin. Sparsity-based moving target localization using multiple dual-frequency radars under phase errors,
SPIE Sensing Technology + Applications. 20-APR-15, Baltimore, Maryland, United States. : ,

12/24/2016 40.00 Michael Leigsnering, Fauzia Ahmad, Moeness Amin, Abdelhak Zoubir,. Multipath exploitation in sparse scene recovery using sensing-through-wall distributed radar sensor configurations,
ICASSP 2015 - 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 19-APR-15, South Brisbane, Queensland, Australia. : ,

12/24/2016 41.00 Michael Leigsnering, Fauzia Ahmad, Moeness Amin, Abdelhak Zoubir. Multipath-aware velocity estimation for sparsity-based through-the-wall radar imaging,
2015 IEEE International Radar Conference (RadarCon). 10-MAY-15, Arlington, VA, USA. : ,

12/24/2016 42.00 Khodour Al Kadry, Fauzia Ahmad, Moeness G. Amin. Moving Target Localization Using Distributed Dual-Frequency Radars and Sparse Reconstruction,
European Signal Processing Conference (EUSIPCO). 31-AUG-15, Nice, France. : ,

12/24/2016 43.00 Khodour AlKadry, Fauzia Ahmad, Moeness Amin. Moving Target Localization Using Distributed Dual-Frequency Radars and Sparse Reconstruction,
European Signal Processing Conference (EUSIPCO). 31-AUG-15, Nice, France. : ,

12/24/2016 46.00 Davide Comite└, Fauzia Ahmad└, Moeness Amin└, Traian Dogaru. Detection of Low-Signature Targets in Rough Surface Terrain for Forward-Looking Ground Penetrating Radar Imaging,
Asilomar Conference on Signals, Systems, and Computers. 08-NOV-15, Pacific Grove, CA. : ,

12/24/2016 47.00 Davide Comite, Fauzia Ahmad, Moeness Amin, and Traian Dogaru. Multi-Aperture Processing for Improved Target Detection in Forward-Looking GPR Applications,
10th European Conference on Antennas and Propagation. 10-APR-16, Davos, Switzerland. : ,

TOTAL: **18**

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received	Paper
01/29/2014 21.00	Eva Lagunas, Moeness Amin, Fauzia Ahmad, Montse Najar. Pattern Matching for Building Feature Extraction, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS (11 2013)
02/19/2016 48.00	Davide Comite, Fauzia Ahmad, DaHan Liao, Traian Dogaru, Moeness Amin. Multi-View Imaging for Low-Signature Target Detection in Rough-Surface Clutter Environment, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING (02 2016)
03/12/2014 23.00	Fauzia Ahmad, Moeness G. Amin, Traian Dogaru. Partially sparse imaging of stationary indoor scenes, EURASIP Journal on Advances in Signal Processing (02 2014)
07/02/2014 26.00	Michael Leigsnering, Fauzia Ahmad, Moeness G. Amin, Abdelhak M. Zoubir. Compressive Sensing Based Multipath Exploitation for Stationary and Moving Indoor Target Localization, IEEE Journal on Selected Topics in Signal Processing (03 2014)
08/12/2013 15.00	Fauzia Ahmad, Moeness Amin, Traian Dogaru. Partially Sparse Image Reconstruction of Stationary Indoor Scenes , Signal Processing (Elsevier) (04 2013)
08/12/2013 16.00	Fauzia Ahmad, Jiang Qian, Moeness Amin. Wall Clutter Mitigation using Discrete Prolate Spheroidal Sequences for Sparse Reconstruction of Indoor Stationary Scenes, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING (07 2013)

TOTAL: **6**

Number of Manuscripts:

Books

Received	Book

TOTAL:

Received Book Chapter

TOTAL:

Patents Submitted

Patents Awarded

Awards

The PI and Co-PI of this project have received the following recognition during the past year:

1. The PI was elected as a member of the Sensor Array and Multichannel (SAM) technical committee of the IEEE Signal Processing Society.

2. The PI was elected member of the Electrical Cluster of the Franklin Institute Committee on Science and the Arts.

2. The CO-PI received the prestigious Humboldt Research Prize.

Graduate Students

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
Davide Comite	0.25
FTE Equivalent:	**0.25**
Total Number:	**1**

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Fauzia Ahmad	0.67	
Moeness Amin	0.08	
FTE Equivalent:	**0.75**	
Total Number:	**2**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00

The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields:...... 0.00

Names of Personnel receiving masters degrees

NAME
Total Number:

Names of personnel receiving PHDs

NAME
Total Number:

Names of other research staff

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

See Attachment

Technology Transfer

The team at Villanova has collaborated with Dr. Traian Dogaru of U.S. Army Research Laboratory (ARL) in Adelphi, Maryland. Dr. Dogaru provided valuable electromagnetic simulation datasets of various through-the-wall and forward-looking ground penetrating radar scenarios to support the investigations in this project. Dr. Dogaru has also co-authored journal articles and conference publications with our team. The team members from Villanova University visited ARL in Adlephi, MD once every year and presented their research findings to several attendees.

Multipath Exploitation and Knowledge Based Urban Radar Imaging using Compressive Sensing

Scientific Progress and Accomplishments

by

Fauzia Ahmad – Principal Investigator
Moeness G. Amin – Co-Principal Investigator

Center for Advanced Communications
Villanova University, Villanova PA 19085

for

Dr. Liyi Dai
Army Research Office
Research Triangle Park, NC 27709-2211

December 23, 2016

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Table of Contents

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1 Statement of the Problem Studied

Detection and localization of stationary and moving targets inside enclosed structures using radar are very pertinent to the Army's needs for meeting the challenges of nonlinear warfare in urban environments [1]-[3]. The most desirable goal is to achieve actionable intelligence in an efficient and reliable manner. This goal is primarily challenged due to the use of wideband signals and large array apertures, resulting in acquisition, storage, and processing of huge data volumes. Compressive Sensing (CS) provides a new perspective for data reduction in radar imaging without compromising the imaging quality [4]-[8]. Towards the objective of providing persistence surveillance in urban environments, such techniques yield reduced cost and efficient sensing operations that allow super-resolution imaging of sparse scenes, thereby culminating in quick turnaround, reliable, and actionable intelligence. Further, producing an image of the indoor scene using fewer observations can be logistically important, as some of the data measurements in space and frequency can be difficult, or impossible to attain.

Detection, localization, and imaging of low-signature subsurface targets under challenging rough ground surface conditions are also highly desirable for providing enhanced situational awareness to warfighters. An FLGPR offers the advantage of standoff sensing for detecting ground targets, but the target responses are more vulnerable to interference scattering arising from interface roughness and subsurface clutter. Enhancing imaging performance through rough surface clutter suppression in forward-looking ground penetrating radar (FLGPR) systems enables low-signature target detection.

In this report, we first exploit the offerings of emerging CS techniques to aid in efficient sensing operations using wideband radar imaging systems for urban sensing applications. We develop appropriate signal models and algorithms for building layout mapping and imaging of stationary and moving targets inside enclosed structures within the CS framework. Our primary contributions for achieving reliable, actionable intelligence under reduced data volume comprise: i) Utilization of change detection based moving target indication for mitigation of clutter and stationary targets, and as such, conversion of populated scenes to sparse scenes of a few moving targets, whereby CS schemes can exploit full benefits of sparsity-driven imaging; ii) Application of the wall-clutter mitigation techniques in conjunction with CS for effective imaging of stationary targets inside enclosed structures; iii) Effective wall clutter suppression by using discrete prolate spheroidal sequences (DPSSs) to represent spatially extended stationary targets, including exterior walls; iv) Utilization of the typical geometric signatures of building interior structures (walls and corners) and prior information about common construction practices to design two sparsifying dictionaries well-suited to the problem of determining the building interior layout; v) Use of a novel type of image descriptor, named correlogram, in a pattern matching scheme for detecting building dominant scatterers under oblique illumination; vi) Exploiting multipath returns to solve the inverse problem of joint localization and velocity estimation of indoor targets; vii) Use of parametric dictionary learning to extend proposed multipath exploitation scheme to cases where perfect knowledge of building interior layout is unavailable; and viii) Development of a modified distributed sparse reconstruction algorithm with efficient communication capability for a distributed through-the-wall radar network. The aforementioned techniques are detailed in Sections 2.1 through 2.8.

The main contributions for low-signature target detection in FLGPR consist of i) A multi-view approach wherein images corresponding to the different views are generated using a tomographic near-field algorithm, followed by a fusion approach based on likelihood ratio tests (LRT) detector to combine the multi-view images for enhanced target detection; and ii) a near-field coherence factor based approach for rough surface clutter mitigation. These techniques for FLGPR are detailed in Sections 2.9 and 2.10.

2 Summary of the Most Important Results

2.1 Sparsity-Based Change Detection for Moving Target Indication

2.1.1 Contribution

We consider sparsity-driven change detection for human motion indication in through-the-wall radar imaging and urban sensing applications, while simultaneously achieving a sizable reduction in the data volume. [9]. Stationary targets and clutter are removed via change detection, which converts a populated scene into a sparse scene of a few human targets moving inside enclosed structures and behind walls. We establish appropriate change detection models for various possible human motions, ranging from translational motions to sudden short movements of the limbs, head, and/or torso. These models permit scene reconstruction within the compressive sensing framework. Results based on laboratory experiments show that a sizable reduction in the data volume is achieved using the proposed approach without a degradation in system performance.

2.1.2 Highlights of the Proposed Techniques

- Change detection is used in lieu of Doppler processing, wherein human detection is accomplished by subtraction of data frames acquired over successive probing of the scene. The frames can be consecutive, dealing with humans exhibiting sudden short motions, or nonconsecutive, with relatively long time difference, for the case in which the human changes its range gate position.
- Change detection mitigates the heavy clutter that is caused by strong reflections from exterior and interior walls and also removes stationary objects present in the enclosed structure, thereby rendering a densely populated scene sparse. As a result, it enables compression in data collections and processing. Scene reconstruction is then achieved using sparsity-driven imaging.
- For each type of motion, we establish an appropriate change detection model that permits formulation of linear modeling with sensing matrices, so as to apply compressive sensing for scene reconstruction.

Detailed description of the proposed techniques for both types of human motion along with supporting results are provided in [9], a reprint of which has been submitted to ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique.

2.1.3 Illustration

In order to illustrate the performance of the sparsity-driven change detection scheme under translational motion, a target moving away from a cement board wall in an empty room along a straight line path was considered. The path is located 0.5m to the right of the center of the scene, as shown in Fig. 1. A wideband pulsed radar system with a single transmitter and an 8-element receive array was used for data collection. The transmitter and receivers were at a standoff distance of 1.19m from the wall. The data collection started with the target at position 1 and ended after the target reached position 3, with the target pausing at each position along the trajectory for a second. Consider the data frames corresponding to the target at position 2 and position 3. Each frame consists of 20 pulses, which are coherently integrated to improve the signal-to-noise ratio. The imaging region (target space) is chosen to be 3m × 3m, centered at

(0.5m, 4m), and divided into 61 × 61 grid points in crossrange and downrange, resulting in 3721 unknowns. The space-time response of the target space consists of 8 × 1536 space-time measurements. Figure 2(a) shows the backprojection-based change-detected image of the scene using all 8 × 1536 data points. We observe that, as the human changed its range gate position during the time elapsed between the two data acquisitions, it presents itself as two targets in the image, and is correctly localized at both of its positions. For sparsity-based change detection, only 5% of the 1536 time samples are randomly selected at each of the 8 receive antenna locations, resulting in 8 × 77 space-time measured data. More specifically, the 77 time samples at each receive location were obtained as the product of the 1536 point time-domain response with a 77 × 1536 measurement matrix, whose elements are randomly chosen ±1 values with a probability of ½. We reconstructed the target space using sparsity-based change detection with 5% data volume one hundred times. For each trial, a different random measurement matrix was used to generate the reduced set of measurements, followed by sparsity-based scene reconstruction. Figure 2(b) depicts the sparsity-based result, averaged over one hundred trials. The higher the intensity of a grid point in this figure, the greater is the number of times that grid point was populated during the 100 reconstruction trials. We observe that, on average, the sparsity-based scheme detects and localizes the target accurately at both positions. Also, compared to the backprojection-based result of Fig. 2(a), the image in Fig. 2(b) is less cluttered. The 'cleaner' image is due to the fact that a sparse solution is enforced by the l_1 minimization employed for scene reconstruction.

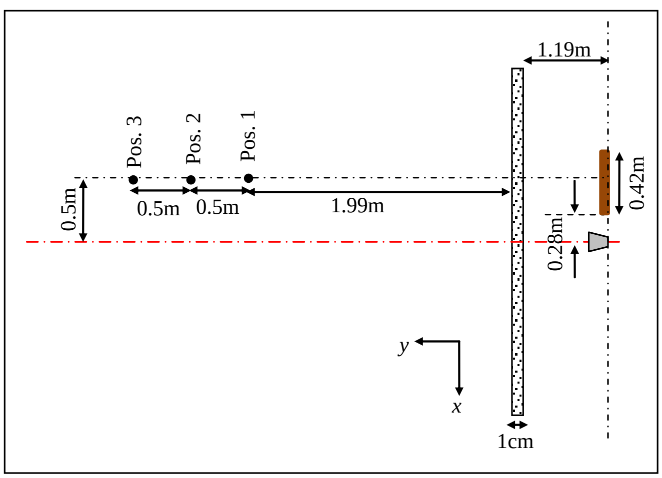
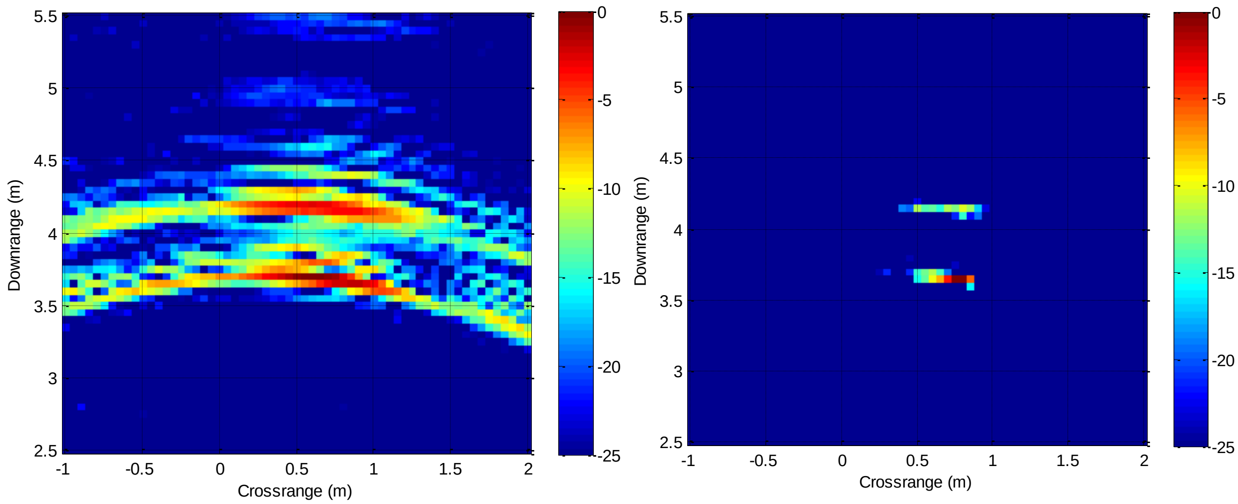


Figure 1. Scene layout for the target undergoing translational motion.



(a) **(b)**

Figure 2. (a) Backprojection based change detection image using the full dataset. (b) Sparsity-based change detection image using 5% of the data volume, averaged over 100 trials.

2.2 Joint Wall Clutter Mitigation and CS Application for Imaging of Stationary Targets

2.2.1 Contribution

Compressive sensing (CS) for urban operations and through-the-wall radar imaging has been shown to be successful in fast data acquisition and moving target localizations [9]-[12]. The research in this area thus far has assumed effective removal of wall EM backscatterings prior to CS application. Wall clutter mitigation can be achieved using full data volume which is, however, in contradiction with the underlying premise of CS. We enable joint wall clutter mitigation and CS application using a reduced set of spatial-frequency observations in stepped-frequency radar platforms [13]. Specifically, we demonstrate that wall mitigation techniques, such as spatial filtering [14] and subspace projection [15], can proceed using fewer measurements. We consider both cases of having the same reduced set of frequencies at each of the available antenna locations and also when different frequency measurements are employed at different antenna locations. The latter casts a more challenging problem, as it is not amenable to wall removal using direct implementation of filtering or projection techniques. In this case, we apply CS at each antenna individually to recover the corresponding range profile and estimate the scene response at all frequencies. In applying CS, we use prior knowledge of the wall standoff distance to speed up the convergence of the OMP for sparse data reconstruction. Real data are used for validation of the proposed approach.

2.2.2 Highlights of the Proposed Techniques

- We examine the performance of the spatial filtering and subspace projection wall mitigation techniques in conjunction with sparse image reconstruction. Only a small subset of measurements is employed for both wall clutter reduction and image formation.
- We consider two cases of frequency measurement distributions over antenna positions. In the first case, the same subset of frequencies is used for each antenna. The other case allows the frequencies to differ from one antenna to another.
- For the subspace projection and spatial filtering methods, we show that when the same subset of frequency measurements is used at each antenna, those two methods maintain their proper performance as their full-data set counterparts. CS techniques for image reconstruction can then be applied with the same reduced measurements but of much higher signal-to-clutter ratio.
- Use of different frequencies at different antenna positions would impede the application of either method. This is because the phase returns across the antenna elements would be different, which deprives the wall mitigation algorithms of the underlying assumption of spatial invariance of the wall clutter. This problem is overcome by first reconstructing the range profile, which is based on l_1 norm minimization. This is performed at each antenna individually. Then, the data of the missing frequencies can be obtained by taking the FFT of the reconstructed range profile at each antenna.
- Once the phase returns corresponding to all original frequencies are estimated, wall mitigation can proceed using spatial filtering, subspace projection, or any other conventional wall mitigation method.
- Sparse data reconstruction is performed using OMP which provides fast l_1 solutions and is appropriate for stepped frequency radar imaging. Since the target is behind the wall, the OMP can be modified such that the iterations corresponding to the range up to the wall can be combined. This allows a quicker inclusion of the target into the reconstruction algorithm.
- We compare OMP with the modified OMP and show the abilities as well as the challenges of performing TWRI with arbitrary data measurements.

Detailed description of the proposed techniques for both cases of having the same reduced set of frequencies at each of the available antenna locations and also when different frequency measurements are employed at different antenna locations are provided in [13], a reprint of which has been submitted to ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique for the case of having the same set of reduced frequencies for a reduced set of antenna locations.

2.2.3 Illustration

A through-the-wall experiment was set up in the Radar Imaging Lab at Villanova University. In this experiment, the side walls were covered with the absorbing material but the 0.31m thick reinforced concrete back wall was left uncovered. For imaging, a 93-element linear array with an interelement spacing of 0.02m was used, which was synthesized using a single horn antenna. The scene was illuminated with a stepped frequency signal of 2 GHz bandwidth centered at 2 GHz, using 641 frequencies with a step size of 3.125 MHz. A 0.2m thick solid concrete block wall was placed 3.13m in front of and parallel to the antenna baseline. The distance between the back face of the front wall and the front of the back wall is 3.76m. A vertical metal dihedral was used as a target, and was placed at (0.3,5.2)m. The size of each face of the dihedral is 0.39m by 0.28m. The region to be imaged is chosen to be 4.9m × 6.4m centered at (0, 4.3)m and divided into 33 × 87 pixels, respectively. The backprojected images using the full data measurements are shown in Fig. 3. In Fig. 3(a), no preprocessing was applied to remove the front wall reflections, whereas in Fig. 3(b), background subtraction was applied. Fig. 3 confirms the need to reduce the front wall clutter in order to detect the presence of the target. Next, we applied the space-frequency subsampling pattern for reduced data volume, which is illustrated in Fig. 4. There are 65 uniformly selected frequencies (20% of 641) and 47 uniformly selected array locations (51% of 93). The l_1 norm reconstructed images obtained with classic OMP are depicted in Fig. 5(a) and Fig. 5(b) for the spatial filter and subspace projection approaches, respectively. They demonstrate that both approaches are effective in reducing the wall reflections without significantly compromising the target image.

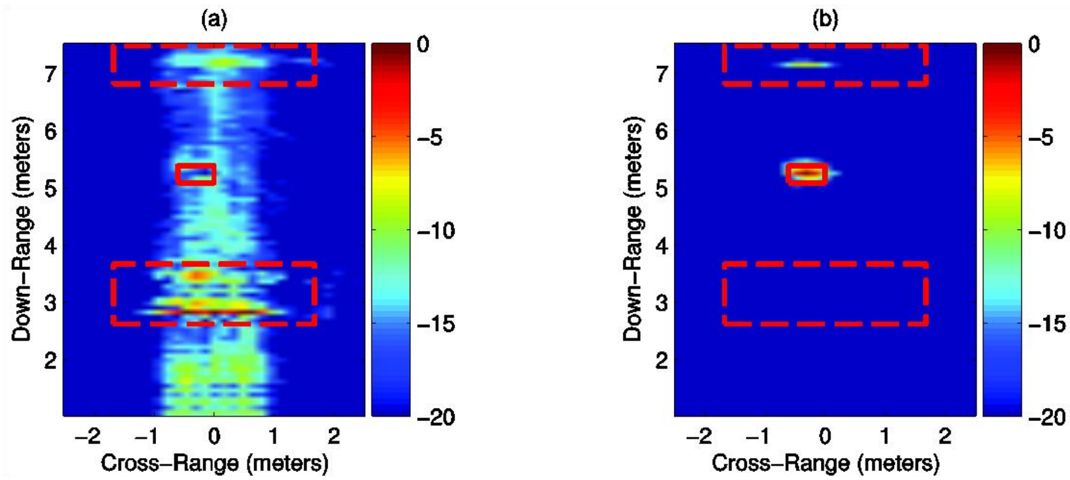


Figure 3. Backprojection images of the scene without absorbing material in the back wall of the room: (a) no preprocessing, (b) after background subtraction.

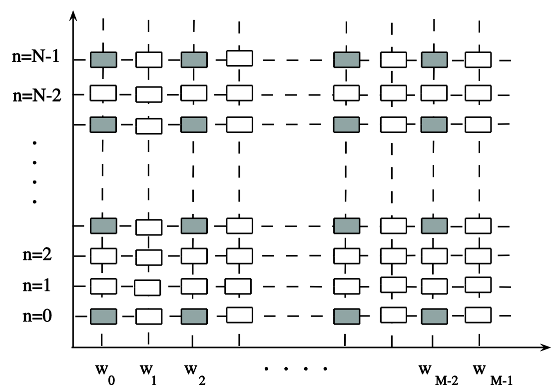


Figure 4. Illustration of an example of subsampling pattern of the conventional configuration for the case of using the same set of reduced frequencies for a reduced set of antenna locations.

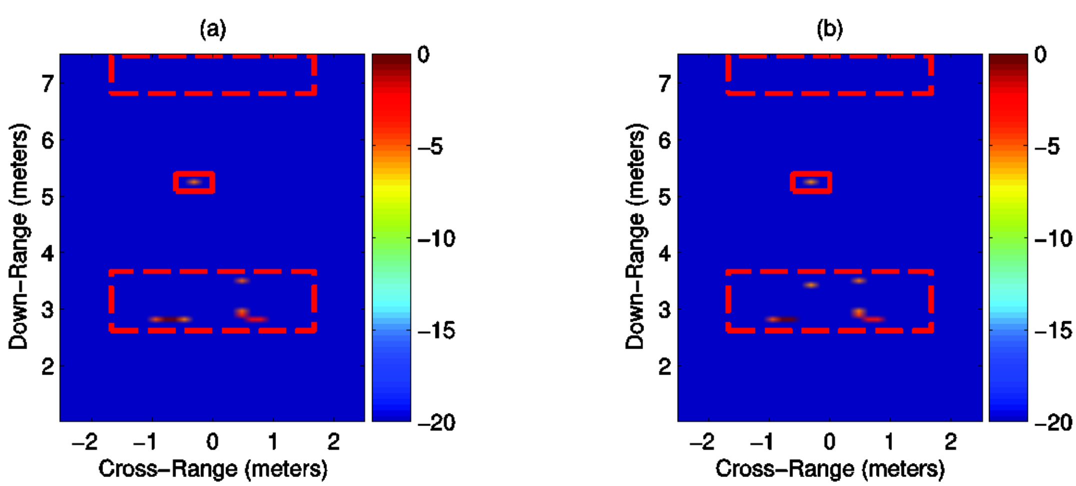


Figure 5. l_1 reconstruction-based imaging results of the scene without absorbing material in the back wall of the room: (a) Spatial filtering - classic OMP, (b) Subspace projection - classic OMP.

2.3 Wall Clutter Mitigation using Discrete Prolate Spheroidal Sequences for Sparse Reconstruction of Indoor Stationary Scenes

2.3.1 Contribution

Detection and localization of stationary targets behind walls is primarily challenged by the presence of the overwhelming electromagnetic signature of the front wall in the radar returns. We use the DPSSs to represent spatially extended stationary targets, including exterior walls. This permits the formation of a linear block sparse model relating the range profile and observation vectors. Effective wall clutter suppression can then be performed prior to sparse signal image reconstruction. We consider stepped-frequency radar with two cases of frequency measurement distributions over antenna positions. In the first case, the same subset of frequencies is used for each antenna in physical or synthetic aperture arrays, while the other case allows different sets of few frequency observations to be available at different antennas. Using experimental data, we demonstrate that the proposed scheme enables sparsity-based image reconstruction techniques to effectively detect and localize behind-the-wall stationary targets from reduced measurements.

2.3.2 Highlights of the Proposed Techniques

- We represent spatially extended stationary targets, including exterior walls, using DPSSs and develop a linear block sparse model relating the range profile and observation vectors corresponding to each antenna location.
- We consider two cases of frequency measurement distributions over antenna positions. In the first case, the same subset of frequencies is used for each antenna. The other case allows the frequencies to differ from one antenna to another.
- We recover the wall return at each antenna location using group sparse reconstruction under the DPSS formulation and subtract the recovered range profile from the actual measurement, thereby mitigating the wall clutter. CS techniques for image reconstruction can then be applied to the wall mitigated returns.

Detailed description of the DPSS based signal model and proposed wall mitigation technique, along with supporting scene reconstruction results are provided in [16], a reprint of which has been submitted to ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique.

2.3.3 Illustration

A stepped-frequency SAR system was used for data measurements in the Radar Imaging Lab at Villanova University. The synthetic linear aperture consisted of 93 uniformly spaced elements, with an inter-element spacing of 0.02 m. The aperture was located parallel to a 0.2 m thick solid concrete block wall at a standoff distance of 3.13 m. The stepped-frequency signal comprised 641 frequencies from 1 to 3 GHz, with a step size of 3.125 MHz. A vertical metal dihedral, located at -0.29 m in crossrange (the origin of the coordinate system is placed at the array center) and 2.05 m away from the other side of the front wall, was used as the target. Each face of the dihedral was 0.39 m × 0.28 m. The side walls were covered with RF absorbing material while the 0.3m thick reinforced concrete back wall was left bare. The distance between the front face of the back wall and the back face of the front wall is 3.76m. The scene layout is depicted in Fig. 6.

The scene to be imaged is chosen to be 4 m × 5.5 m centered at (0, 4.75) m and divided into 33×77 pixels. Fig. 7 depicts the image corresponding to the full raw dataset obtained with backprojection. In addition to the wall reverberation, the antenna ringing is clearly visible in Fig. 7 at downranges prior to the front wall. For the reduced data volume, we randomly selected 20% of the antenna locations with a different set of randomly chosen 20% frequencies at each chosen antenna. Figures 8(a), 8(b), and 8(c) show the sparse reconstruction images after wall clutter mitigation corresponding to subspace projection [13], Fourier basis, and DPSS basis, respectively. Clearly, the DPSS based scheme successfully removed both the antenna ringing and the wall, thereby allowing the subsequent sparse reconstruction to localize the target and the back wall. The Fourier basis could not manage to suppress all of the wall clutter and antenna ringing, and as a result, the reconstruction exhibits a high degree of instability. For the subspace projection based wall clutter mitigation scheme of [13], the reduced data volume is not sufficient to recover the range profile accurately at each antenna location. As a result, the corresponding reconstructed image after wall mitigation is unable to detect the target.

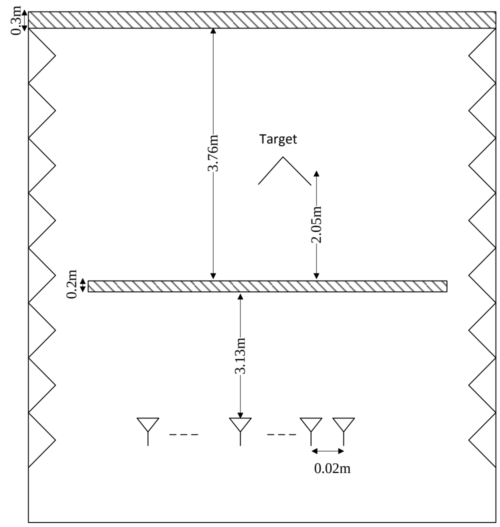


Figure 6. Scene Layout.

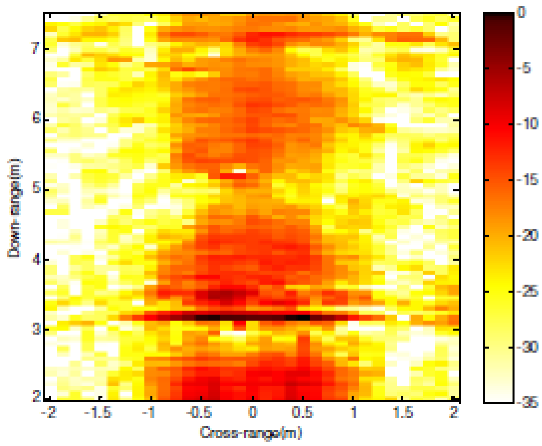
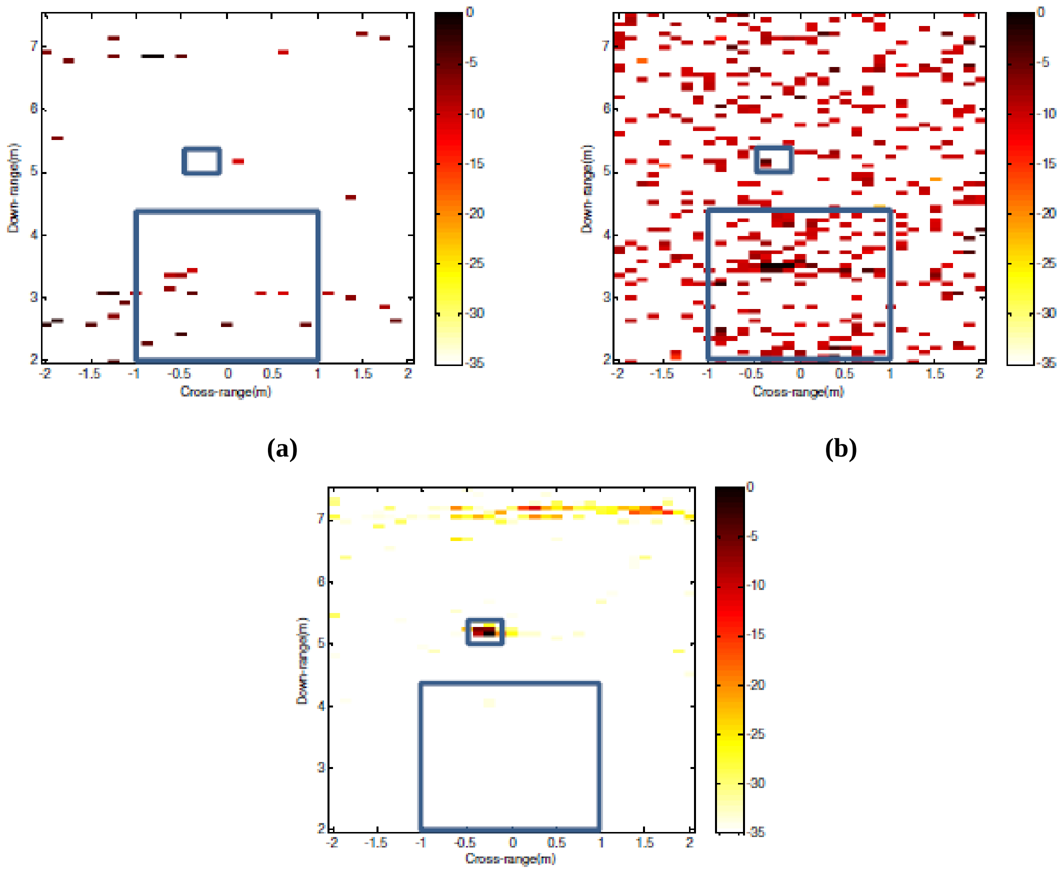


Figure 7. Reconstructed backprojection image using the full raw dataset.

2.4 Determining Building Interior Structures Using Compressive Sensing

2.4.1 Contribution

We consider imaging of building interior structures using CS with applications in urban sensing and through-the-wall radar imaging. We consider a monostatic synthetic aperture radar imaging system employing stepped-frequency waveform. The proposed approach exploits prior information of building construction practices to form an appropriate sparse representation of the building interior layout. We devise a dictionary of possible wall locations, which is consistent with the fact that interior walls are typically parallel to perpendicular to the front wall. The dictionary accounts for the dominant normal angle reflections from exterior and interior walls for



(a) **(b)**

(c)

Figure 8. Sparse reconstruction results using different reduced frequency set at each employed antenna (4% of the total data volume): (a) CS based subspace projection approach, (b) Fourier basis, (c) DPSS basis.

the monostatic imaging system. Sparse reconstruction techniques are applied to a reduced set of observations to recover the true wall positions. Additional information about interior walls can be obtained using a dictionary of possible corner reflectors, which is the response of the junction of two walls. Supporting results based on simulation and laboratory experiments are provided. It is shown that the proposed sparsifying basis outperforms the conventional through-the-wall CS model, the wavelet sparsifying basis, and the block sparse model for building interior layout detection.

2.4.2 Highlights of the Proposed Techniques

- We exploit the typical geometric signatures of building interior structures (walls and corners) and prior information about common construction practices to design two sparsifying dictionaries well-suited to the wall and corner detection problems.

- We first use the sparsifying dictionary based on possible wall locations to infer positions of walls parallel to the radar scan direction using only a small subset of measurements.
- We then obtain more information regarding the junctions between parallel and perpendicular walls following the sparsifying dictionary based on dihedral reflection response.
- Sparse reconstruction in each case is performed using OMP, which provides fast l_1 solutions and is appropriate for stepped frequency radar imaging.

Detailed description of the proposed techniques including the structure of the wall and corner sparsifying dictionaries are provided in [17], a reprint of which has been submitted to ARO. Below, we demonstrate through a simulation example the performance capabilities of the proposed technique for determining building interior structures.

2.4.3 Illustration

A stepped-frequency signal consisting of 335 frequencies covering the 1 to 2 GHz frequency band was used for interrogating the scene. A monostatic synthetic aperture array, consisting of 71-element locations with an inter-element spacing of 2.2 cm, was employed. The array was located parallel to a 1.6m-wide front wall, and centered at 0 m in crossrange at a standoff distance of 2.42 m. The scene behind the front wall contained two interior walls, a back wall, and a single point target. The first interior wall extended from -0.78 m to -0.29 m in crossrange at a downrange of 3.37 m, while the second wall was located at 5.12 m downrange, extending from 0.29 m to 0.78 m in crossrange. The 1.6 m wide back wall was located at 6.24 m and was aligned with the front wall in crossrange. To simulate different wall materials, we considered different reflectivities for interior and exterior walls. The two interior walls and the back wall have corner reflectors on their extremities to emulate the junctions between parallel and perpendicular walls. The point target was located at (0.02, 4.24) m. Fig. 9 depicts the geometry of the simulated scene. The region to be imaged is chosen to be 5.65m (crossrange) × 4.45m (downrange), centered at (0, 4.23) m, and is divided into 128 × 128 pixels. For sparsity-based imaging, we consider only 6.4% of the full data volume (25% uniformly selected frequencies and 25% uniformly chosen sensor locations). Fig. 10(a) and Fig. 10(b) show the recovered CS images from the wall detection step and the corner detection step, respectively. It is evident that the image produced by the proposed wall detector, which is shown in Fig. 10(a), has adequately reconstructed the structure of the building. Wall corner detections, as shown in Fig. 10(b), refine the detection of building structures by indicating the extents of the walls detected in Fig. 10(a).

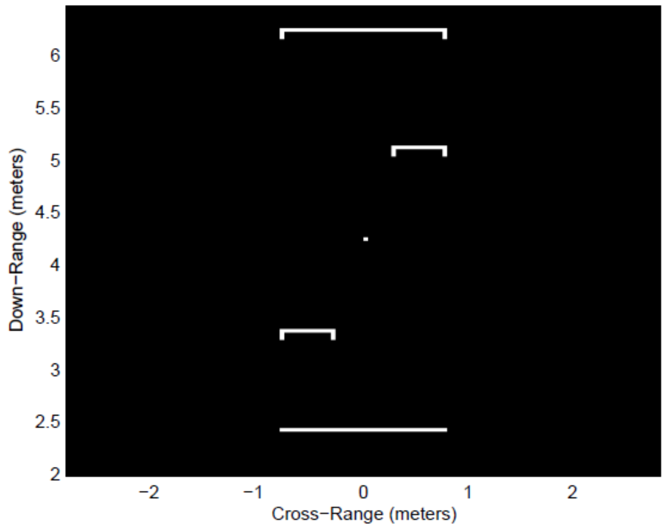


Figure 9. Geometry of the simulated scene.

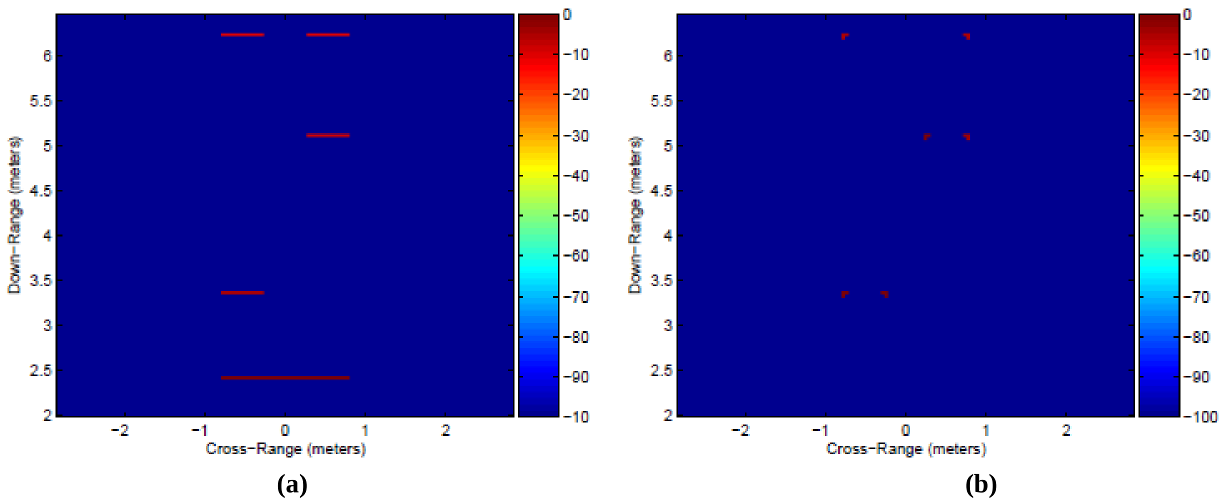


Figure 10. Reconstructed image from the recovered sparse vector using OMP and 6.4% data: (a) Proposed approach for wall detection, (b) Proposed approach for wall detection.

2.5 Pattern Matching for Building Feature Extraction

2.5.1 Contribution

The problem of detecting building dominant scatterers using a reduced number of measurements is addressed with applications to through-the-wall radar (TWR) and urban sensing. We consider oblique illumination, which specially enhances the radar returns from the corners formed by the orthogonal intersection of two walls. We use a novel type of image descriptor, named correlogram, which encodes information about spatial correlation of complex amplitudes of each TWR image pixel. The proposed technique compares the known correlogram of the scattering response of an isolated canonical corner reflector with the correlogram of the received radar signal. The feature-based nature of the proposed detector enables corner separation from other indoor scatterers, such as humans. Numerical electromagnetic (EM) data is employed to show that the use of correlograms makes the detection performance superior to that of either using raw signal matching [17], [18] or image matching [19].

2.5.2 Highlights of the Proposed Techniques

- We exploit the typical scattering signatures of interior building corners. We construct a reference correlogram matrix, which encodes information about the spatial correlation of the image complex amplitudes, for an isolated canonical corner present at a particular pixel location.
- A similarity function is used to measure the reference corner contribution contained in the correlogram of the received radar returns.
- The correlogram matching procedure is conducted for all pixel locations of the reference corner in the region of interest and can be applied to reduced number of measurements.

Detailed description of the proposed technique is provided in [20], a reprint of which has been submitted to ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique.

2.5.3 Illustration

The EM response of a three-room building was generated with FEKO Geometric Optics solver in conjunction with the OPTFEKO options [21]. The simulated scene geometry is depicted in Fig. 11(a). The walls are 20 cm thick and made of solid concrete with permittivity = 6. A PEC sphere of 15 cm diameter is located at (0.02,4.24)m. A stepped-frequency signal consisting of 201 frequencies covering the 1 to 2 GHz frequency band was used for interrogating the scene. An 8-element monostatic line array with an inter-element spacing of 53 cm was used. An oblique illumination of the scene is used to avoid wall returns while preserving the important corner features. The angular tilt of the array baseline is 25°. In this case, only the upper-left corners of the three rooms are expected to produce strong scattering responses for most, if not all, of the antenna elements. The concave sides of the remaining corners are either facing away from the array or only visible to a small number of antenna elements. We, therefore, focus on the detection of these three corners. The region to be imaged is chosen to be 3.5 m × 3.9 m, centered at (0.11, 4.97) m, and is divided into 100 × 100 pixels. The backprojected images using the full data measurements is shown in Fig. 11(b). Although the corners of interest are visible in the image (indicated by white rectangles), it is difficult to discriminate them from other scatterers and clutter even when the full data set is considered. For corner detection with reduced data, we consider only 101 uniformly selected frequencies. Fig. 12(a) shows the image obtained with the proposed correlogram matching approach. Clearly, the proposed approach has detected the three corners and is less cluttered than the full-data image in Fig. 12(b). For comparison, Fig. 12(b) shows the results obtained with the CS-based reconstruction using overcomplete dictionary [17]. OMP was used in this case with the total number of iterations set to 200. Although Fig. 12(b) provides a relatively clean image with few dominant pixels, some of the strongest ones are outside the white rectangles indicating the corner locations.

2.6 Compressive Sensing Based Multipath Exploitation for Stationary and Moving Indoor Target Localization

2.6.1 Contribution

Compressive sensing based multipath exploitation has been successfully applied to stationary indoor scenes in through-the-wall radar imaging [22]. The benefits of using significantly reduced data are also desirable for moving targets. Hence, we bring CS based multipath exploitation to the nonstationary target domain and are able to treat moving and stationary targets simultaneously. In general, multipath propagation has adverse effects on the image quality. However, by using proper modeling, multipath can be used to one's advantage. We apply CS to both stationary and moving targets under interior wall scatterings. Assuming knowledge of the room geometry, we solve the inverse problem of joint localization and velocity estimation of the targets in an indoor multipath environment. We develop an effective method that permits reconstruction of the scene from a few measurements. We also propose a scheme to estimate and correct wall position errors that introduce distortions in the reconstruction. Effectiveness of the proposed methods is demonstrated using both simulated and experimental data.

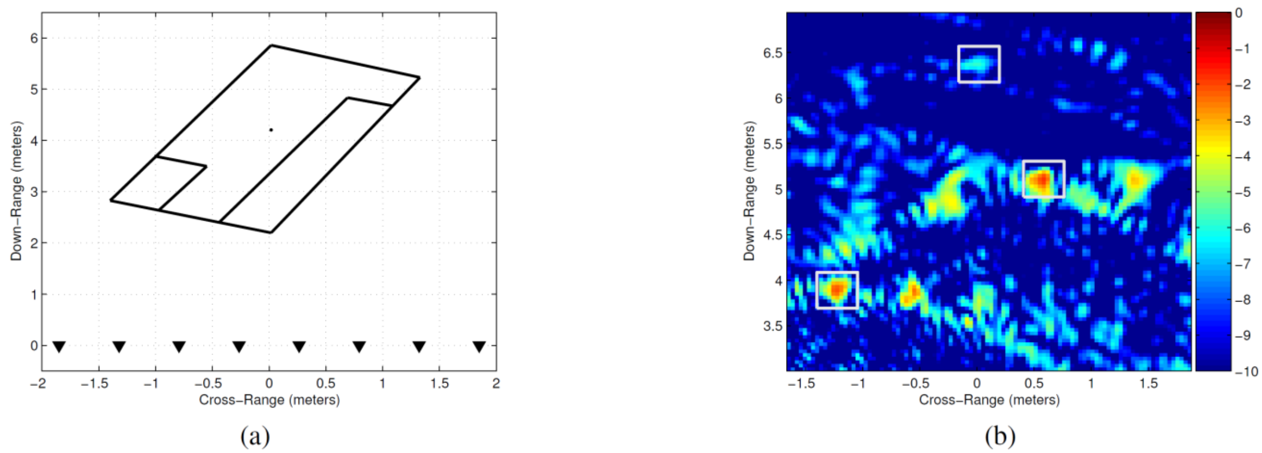


Figure 11. (a) Scene geometry; (b) Backprojection image considering full data volume.

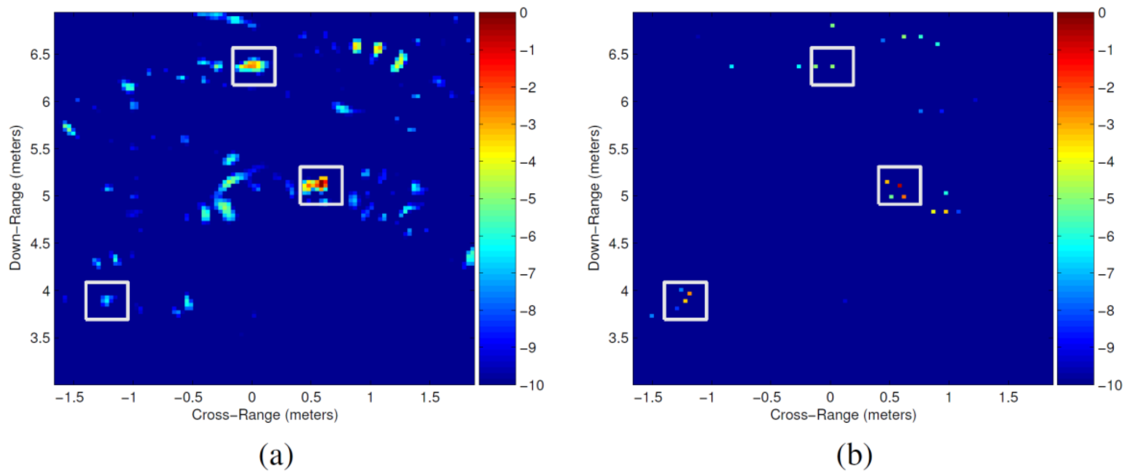


Figure 12. Images using reduced data volume; (a) Correlogram matching; (b) CS-based reconstruction using overcomplete dictionary.

2.6.2 Highlights of the Proposed Techniques

- Assuming knowledge of the room geometry, we calculate the propagation delays corresponding to different multipath returns for each assumed target location and velocity. Multipath returns associated with the same wall are grouped together and represented by an individual dictionary.

- A multiplicity of 4-dimensional (downrange, crossrange, horizontal and vertical velocities) scene reflectivity maps corresponding to the multipath returns associated with various walls are jointly recovered through application of group sparse reconstruction strategy. A composite 4-dimensional image is obtained by noncoherent combining of the reconstructed reflectivity maps.

- We also tackle the problem of multipath exploitation under imprecisely known interior wall locations. We apply an image quality metric to a series of reconstruction results corresponding to different assumed wall positions, and mitigate the adverse effects of wall position uncertainties by opting for the reconstruction that optimizes the metric.

Detailed description of the proposed techniques for stationary and moving target localization in an indoor multipath environment along with supporting results are provided in [23], a reprint of which has been submitted to ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique.

2.6.3 Illustration

Simulations were performed for a wideband pulse-Doppler multistatic radar with a 4-element uniform linear array of length 1 m. Each array element can be used for both transmission and reception. A modulated Gaussian pulse, centered around 2 GHz, with a relative bandwidth of 50% is transmitted. The pulse repetition interval is set to 10 ms and 15 pulses are processed coherently. At the receiving side, 150 fast time samples in the relevant interval, covering the target and multipath returns, are taken at a sampling rate of 4 GHz. The front wall is modeled with 20 cm thickness and relative permittivity of 7.66, and is located parallel to the array at a distance of 3 m. Two side walls are considered at 2 m in crossrange, each of which causes 3 different multipath returns per target. There are, in total, 4 first order multipath returns and 2 second order quasi-monostatic multipath returns per target, which are all considered to be 6 dB weaker than the direct path. Hence, in total, there are 7 paths per target contributing to the received signal. We assume that the returns from the front wall have been properly suppressed. We neither consider any wall returns nor any multipath from the back wall located at 6 m downrange. The imaged region extends 6 m in crossrange and 4 m in downrange and is centered around a point in the broadside direction of the array at 4 m downrange. The scene of interest is spatially discretized into a 32×32 pixel grid. The target velocities are discretized on a 5×7 crossrange by downrange grid, spanning target velocity components of ± 0.9 m/s. We consider two stationary targets residing at coordinates (0.5, 3.7) m and (-1.5, 3.7) m and two moving targets at (0.5, 4.7) m and (-1.5, 4.7) m, respectively. The moving targets are assumed to be 8 dB weaker than the stationary targets and possess respective velocities (-0.45, 0) m/s and (0, 0.3) m/s. We assume that all targets are visible via all 7 possible paths. The conventional beamforming results using full measurements are shown in Fig. 13. The image appears very cluttered due to the multipath responses and the moving targets cannot be discerned. Next, we show in Fig. 14 the multipath exploitation based group sparse reconstruction using 7% of the full Nyquist sampled measurements, averaged over 20 Monte Carlo runs. It is evident that both the locations and the velocities of the four targets have been correctly recovered. The ghost targets have been largely suppressed and only a few weak clutter pixels remain. The clutter can mostly be attributed to the high correlation in the dictionary for neighboring crossrange velocities, leading to a certain "leakage". Overall, the multipath exploited CS reconstruction features a very clean and accurate high-resolution image.

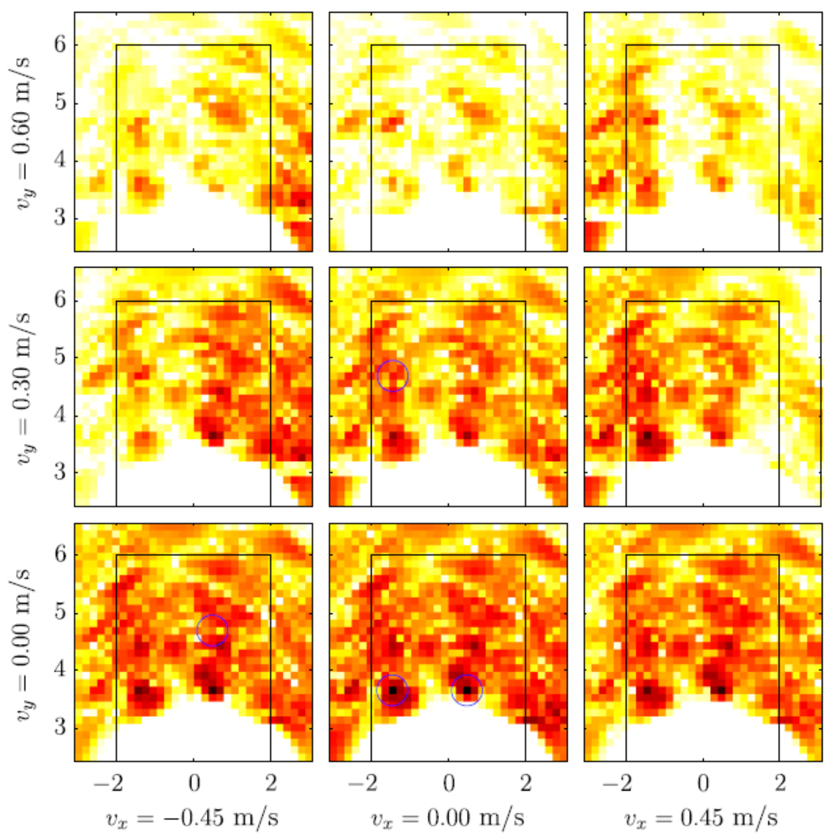


Figure 13. Beamforming result using full data.

2.7 Parametric Dictionary Learning for Sparsity-Based TWRI in Multipath Environments

2.7.1 Contribution

Sparsity-based multipath exploitation is a promising method to eliminate ghost targets in through-the-wall radar images and utilize the additional energy in secondary reflections [22],

[23]. The applicability of existing methods, however, is limited due to the assumption of perfectly known geometry of building interiors. We develop a parametrized multipath signal model that captures unknown or partially known wall locations. This model is used in the proposed joint image reconstruction and wall position estimation method. In order to further improve practicability in realistic scenarios, a reconstruction method based on deployment of multiple small aperture radar modules is discussed. To this end, we analyze theoretical performance bounds for co-located and distributed placements of the various modules. Supporting results based on simulated and experimental lab data are provided.

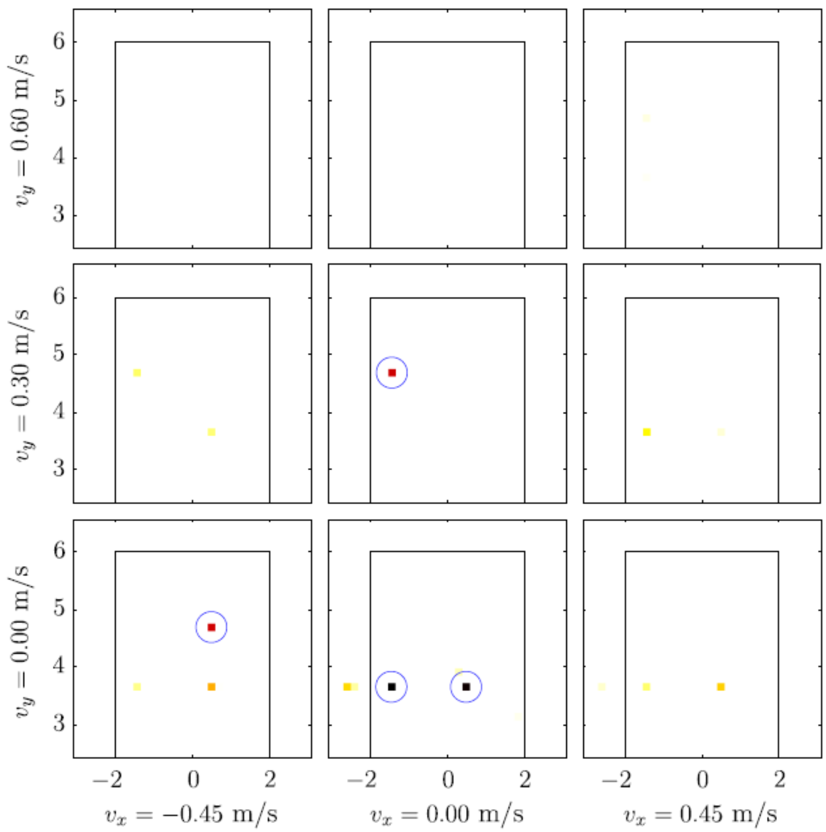


Figure 14. Sparse reconstruction using 7% of the data volume.

2.7.2 Highlights of the Proposed Techniques

- Both collocated and distributed configurations of a modular multistatic radar system, comprising several man-portable through-the-wall radar modules, are considered. We assume that the radar modules cooperate with each other and their measurements are combined in a central processing station.

- A parametrization of the wall locations in the signal model is proposed to accommodate uncertainties in the knowledge of the scattering environment. This leads to a joint optimization problem to simultaneously solve for the wall locations and perform a ghost-free scene reconstruction at the central processing station.
- Due to the high non-linearity and non-convexity of the optimization problem, a nested approach is adopted, wherein the convex scene reconstruction problem is solved for fixed wall locations in an iterative fashion, with the wall locations updated at each step.

Detailed description of the proposed techniques for stationary target localization in an indoor multipath environment under wall location uncertainties along with supporting results are provided in [24], a reprint of which has been submitted to ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique.

2.7.3 Illustration

We present experimental results for a wideband real aperture pulse-Doppler radar with one transmitter and a uniform linear array with eight receivers and an interelement spacing of 6 cm. This is equivalent to a co-located configuration of two modules, each with a single transmitter and a 4-element uniform linear array of receivers, but with only one of the transmitters in operation. The data has been collected in a semi-controlled environment at the Radar Imaging Lab, Villanova University. The transmit waveform is a modulated Gaussian pulse with center frequency of 3 GHz and 100% relative bandwidth. We recorded 768 fast time samples at a sampling rate of 7.68 GHz and then gated out the early and late returns to clean the data, resulting in 153 samples over the interval of interest. The transmitter and the receive array were placed on the same baseline with a lateral spacing of 29.2 cm and the distance of the transmitter to a 0.3 m thick reinforced concrete side wall was 62 cm. The placement of a front wall in the scene was omitted for experimental convenience. We consider four propagation paths, i.e. the direct path, two paths with a single reflection at the side wall and one with double reflection at the side wall. The scene consists of a single aluminum pipe placed at 3.4 m downrange directly in front of the transmitter, as shown in Fig. 15. As a reference, the benchmark result where the actual wall position has been used is shown in Fig. 16(a). The reconstruction result with an erroneous wall location is shown in Fig. 16(b), whereas the proposed wall correction based result is shown in Fig. 16(c). The dashed line depicts the assumed and estimated wall locations in Figs.

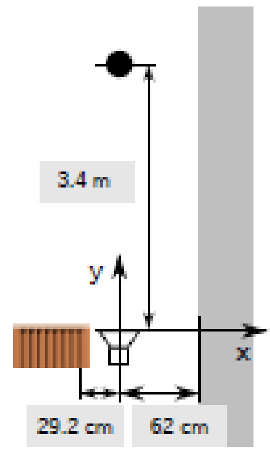


Figure 15. Scene geometry for the lab experiment.

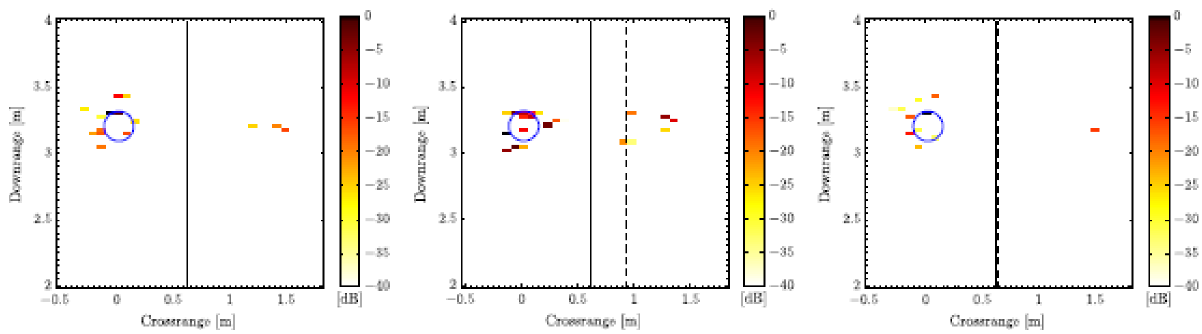


Figure 16. Reconstruction using experimental data with one unknown side wall. (a) Benchmark; (b) Wall error; (c) proposed scheme.

16(b) and 16(c), respectively. We observe that the reconstruction fails when the assumed wall location is incorrect. Using the proposed method, the wall location has been accurately estimated and the corresponding reconstruction yields an image on par with the benchmark.

2.8 Distributed Greedy Signal Recovery for Through-the-Wall Radar Imaging

2.8.1 Contribution

Distributed radar networks for through-the-wall radar imaging have the advantage of flexibility, high accuracy and fault tolerance. We propose a modified distributed orthogonal matching pursuit (MDOMP) algorithm with efficient communication scheme for sparse scene reconstruction in TWRI applications. The communication costs, computational complexity, and reconstruction performance are analyzed for the proposed algorithm and compared with existing distributed sparse reconstruction methods. Simulated and experimental data are used to demonstrate that the MDOMP provides desirable performance at moderate communication and computation costs.

2.8.2 Highlights of the Proposed Techniques

- In each radar unit, an image of the scene will be reconstructed while cooperating with other units.
- In every radar unit at each iteration, a communication step is performed, where all units exchange the observation vector with each other; the observation vector is computed by projecting the residual to the dictionary candidate.
- Every unit selects the index corresponding to the largest element in the summation of all observation vectors and updates the set of indices.
- The remaining part of the algorithm is similar to OMP.
- Censoring has also been proposed to reduce the communication load, where the units transmit only the T largest values and corresponding indices of the observation vector. Every unit determines the indices of maximum value of the superposition of the shared sparse observation vectors and updates the set of indices.

Detailed description of the proposed technique and analysis of the associated communication costs along with supporting results are provided in [25], a reprint of which has been submitted to ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique.

2.8.3 Illustration

We evaluate distributed greedy reconstruction using through-the-wall radar measurements recorded in the Radar Imaging Lab at Villanova University, USA. A metal sphere of 14 in diameter (left) and a gallon plastic jug filled with saline solution (right) are placed behind a concrete block wall of thickness 14 cm and dielectric constant of 7.6632. The two targets are placed on styrofoam pedestals with heights 1.61 m and 0.99 m, respectively. The radar units, each comprising a 0.26 m long monostatic uniform linear array with five elements, are placed at a standoff distance of 1.05 m from the front wall at 1.13 m height. The center-to-center separation between the two units is 0.42 m. A stepped frequency signal is used with 801 equally spaced steps between 700 MHz and 3.1 GHz. The two units are employed for data collection sequentially. The reconstruction corresponding to distributed OMP (DOMP) [26] is depicted in Fig. 17(a), while Fig. 17(b) shows the result of proposed MDOMP with a censoring level of 100. The true target locations are indicated with circles in these figures. The sparsity level is set to 5 for both cases. We observe that both DOMP and censored-MDOMP algorithms reconstruct the sphere correctly. However, only censored-MDOMP is able to reconstruct the weaker target (saline jug) at the true location.

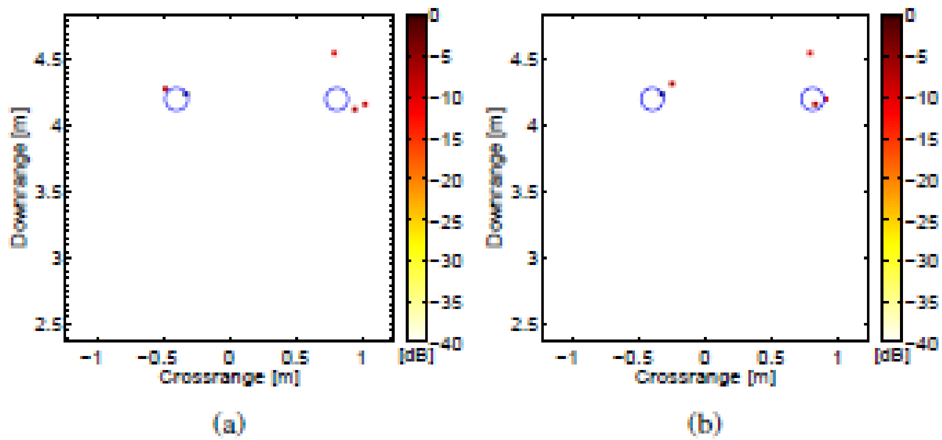


Figure 17. Results based on experimental data. (a) Distributed OMP; (b) MDOMP with censoring.

2.9 Multi-View Imaging for Low-Signature Target Detection in Rough-Surface Clutter Environment

2.9.1 Contribution

Forward-looking ground penetrating radar permits standoff sensing of shallow in-road threats. A major challenge facing this radar technology is the high rate of false alarms stemming from the vulnerability of the target responses to interference scattering arising from interface roughness and subsurface clutter. We present a multi-view approach for target detection in FL-GPR. Various images corresponding to the different views are generated using a tomographic algorithm, which considers the near-field nature of the sensing problem. Further, for reducing clutter and maintaining high cross-range resolution over the imaged area, each image is computed in a segment-wise fashion using coherent integration over a suitable set of measurements from multiple platform positions. We employ two fusion approaches based on likelihood ratio tests detector to combine the multi-view images for enhanced target detection. The superior performance of the multi-view approach over single-view imaging is demonstrated using electromagnetic modeling data.

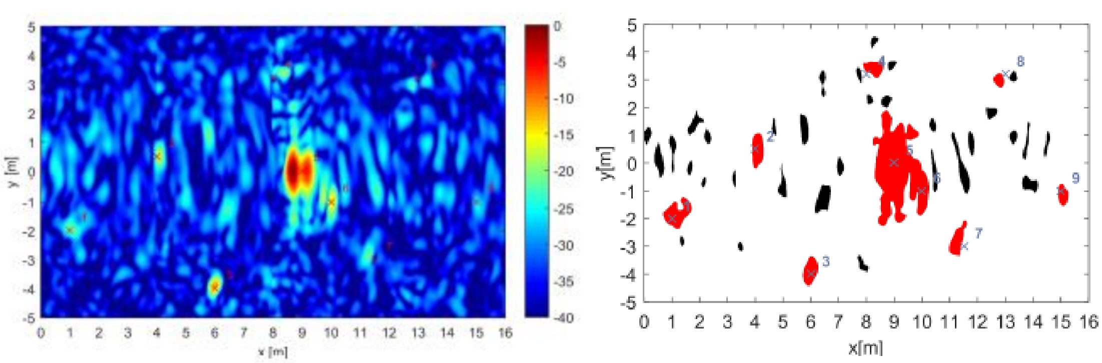
2.9.2 Highlights of the Proposed Techniques

- We consider an FLGPR equipped with a multistatic array, which is mounted on a ground-based moving platform. In essence, we exploit the multi-view intrinsic nature of the considered configuration, which arises due to the ability to collect a number of measurements from different positions along the platform path.
- We employ a tomographic algorithm for image formation, which takes into account the near-field nature of the sensing problem. Further, the investigation domain is divided into segments and the image corresponding to each segment for a specific viewpoint is computed using coherent integration of measurements over several platform positions. The sets of platform positions being integrated for the various segments are chosen to maintain the same standoff distance across all segments in each image. This aids in avoiding deterioration of the crossrange resolution across the entire imaging area, which in turn, prevents large variations in the statistics of the FL-GPR images.
- We employ two strategies, both based on likelihood ratio tests (LRT), for the fusion of images obtained from different views. The first approach performs simultaneous detection and fusion, whereas the latter performs detection on individual images, followed by fusion. Both strategies take advantage of the clutter diversity provided by the multiple views, since the clutter gives rise to different image-domain signatures when observed from different points of view.

Detailed description of the proposed image formation and fusion techniques along with supporting results based on electromagnetic modeled data are provided in [27], a reprint of which has been submitted to ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique.

2.9.3 Illustration

We consider a vehicle-borne stepped-frequency radar system, equipped with a 2 m wide antenna array comprising two transmit and 16 receive elements, mounted on top of the vehicle at respective heights of 2 m and 1.9 m. Full aperture measurements, corresponding to all 32 transmit-receive channels, are generated by alternating between the left and right transmit elements over two consecutive platform positions. The scene to be imaged includes a rough ground surface and a collection of nine targets, buried or placed on the surface. The ground is modeled as a non-dispersive and non-magnetic homogeneous dielectric medium with effective relative dielectric constant = 6 and conductivity = 10 mS/m. The rough surface of the interface separating the upper and lower dielectric half-space is described by a 2-D random process with Gaussian statistics, characterized by its root mean square height of 0.8 cm, and correlation length of 14.26 cm. The entire terrain area has an extent of 38 m by 10 m, with the radar platform moving along a 2 m wide strip of length 33 m, starting from x = -22 m and ending at x = 11 m. The image area containing all nine targets is 16 m by 10 m. The stepped-frequency signal covers the 0.3 - 1.5 GHz frequency band in 6 MHz increments. We consider a total of 100 successive platform positions, spaced 0.333 m apart along the x–direction. In order to suppress the rough surface clutter, we coherently integrate eight full aperture measurements, with two neighboring full aperture measurements separated by four platform positions. Fig. 18(a) depicts the reconstruction result for the 9-target scene from one of the viewpoints and the corresponding binary output of the LRT detector is shown in Fig. 18(b). The red spots indicate correct detections, whereas black spots are false alarms. Although all nine targets have been detected, a significant number of false alarms has also been obtained. Fig. 19(a) depicts the binary image obtained by considering 11 multi-view images and performing fusion and detection at the same time through a multi-view LRT detector (scheme 1). Comparing to the single-view result of Fig. 18(b), we conclude that only a slight performance improvement is achieved, with the number of false alarms unsatisfactory. Fig. 19(b) presents the fusion result for fusion scheme 2. That is, we apply the LRT detector to individual images. The resulting binary images are then fused using pixel-wise multiplication. We observe that a significant number of false alarms have been eliminated and all the targets are still detected.



(a) (b)

Figure 18. (a) Segment-wise reconstructed image. (b) Corresponding binary image for a 0.05 false alarm rate.

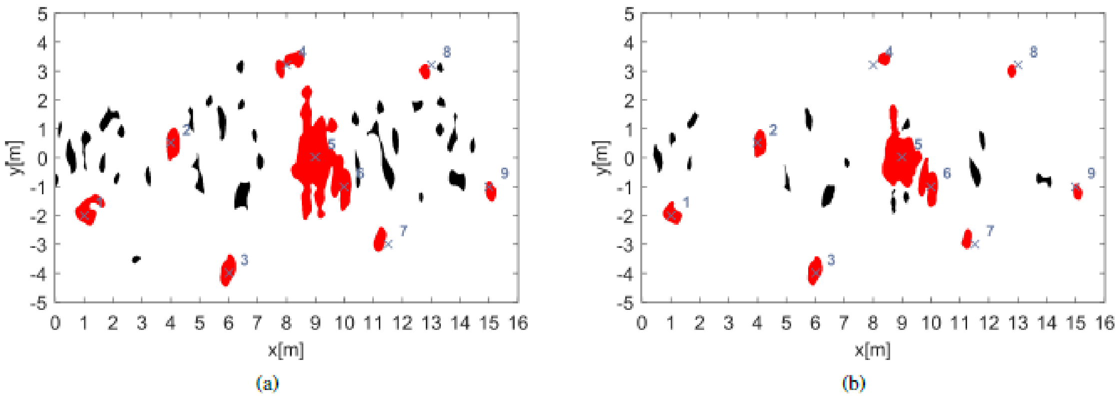


Figure 19. Binary image obtained by implementing (a) fusion scheme 1 and (b) fusion scheme 2), both for false alarm rate= 0.05.

2.10 Coherence Factor for Rough Surface Clutter Mitigation in Forward-Looking GPR

2.10.1 Contribution

We employ a near-field coherence factor for rough surface clutter mitigation in forward-looking ground penetrating radar imagery. The coherence factor is first used to generate a "coherence map" of the region of interest (ROI). Then, a pixel-by-pixel multiplication of a tomographic image of the ROI with the coherence map is performed to generate an enhanced image. Electromagnetic modeled data of shallow buried targets is used to demonstrate the effectiveness of the proposed approach.

2.10.2 Highlights of the Proposed Techniques

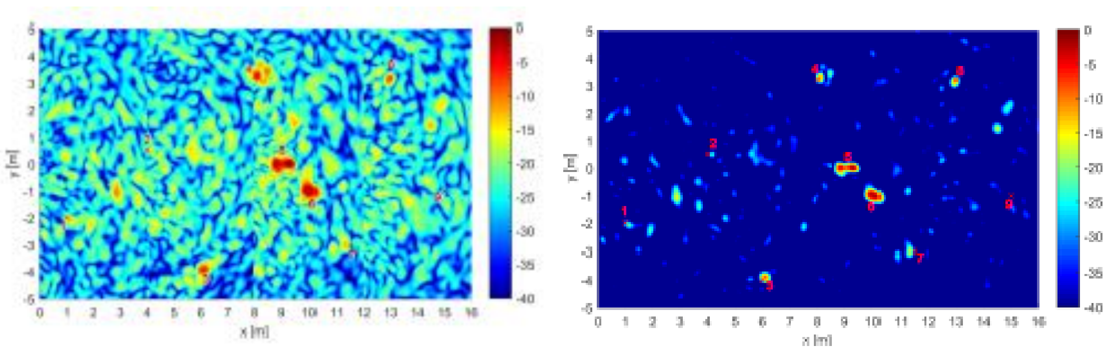
- We consider an FLGPR equipped with a multistatic array, which is mounted on a ground-based moving platform.
- We first employ a matched filtering formulation of microwave near-field tomographic technique to generate an image of the ROI.
- The CF is then used to generate a "coherence map" of the ROI, which assumes small values for low coherence image regions corresponding to rough surface clutter.
- Finally, a pixel-by-pixel multiplication of the tomographic image of the ROI with the coherence map is performed to generate a clutter-suppressed image.

Detailed description of the proposed matched filtering based tomographic image formation and coherence factor based clutter suppression scheme along with supporting results based on electromagnetic modeled data are provided in [28], a reprint of which has been submitted to

ARO. Below, we demonstrate through an example the performance capabilities of the proposed technique.

2.10.3 Illustration

We consider the same system and simulation parameters as described in Section 2.9.3, with the exception of the ground root mean square height of 1.6 cm. Fig. 20(a) depicts the tomographic image obtained by integrating measurements from two full apertures. The clutter generated by the rough surface is clearly visible in the image and renders subsequent target detection a difficult task. The enhanced image after coherence factor based correction is shown in Fig. 20(b). Clearly, the clutter has been significantly mitigated, which would in turn lead to an improved detection performance.



(a) (b)

Figure 20. (a) Tomographic image of the ROI. (b) Coherence factor based enhanced image.

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