R3-B.2: Advanced Imaging & Detection of Security Threats Using Compressive Sensing

I. PARTICIPANTS

<table>
<thead>
<tr>
<th>Faculty/Staff</th>
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</thead>
<tbody>
<tr>
<td>Name</td>
<td>Title</td>
</tr>
<tr>
<td>Jose Martinez</td>
<td>PI</td>
</tr>
<tr>
<td>Hipolito Gomez Sousa</td>
<td>Post-Doc</td>
</tr>
<tr>
<td>Juan Heredia Juesas</td>
<td>Post-Doc</td>
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<table>
<thead>
<tr>
<th>Graduate, Undergraduate and REU Students</th>
<th>Degree Pursued</th>
<th>Institution</th>
<th>Month/Year of Graduation</th>
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<tbody>
<tr>
<td>Galia Ghazi</td>
<td>PhD</td>
<td>NEU</td>
<td>8/2017</td>
</tr>
<tr>
<td>Luis Tirado</td>
<td>PhD</td>
<td>NEU</td>
<td>3/2018</td>
</tr>
<tr>
<td>Ali Molaei</td>
<td>PhD</td>
<td>NEU</td>
<td>5/2018</td>
</tr>
<tr>
<td>Richard Obermeier</td>
<td>PhD</td>
<td>NEU</td>
<td>12/2018</td>
</tr>
<tr>
<td>Chang Liu</td>
<td>PhD</td>
<td>NEU</td>
<td>12/2018</td>
</tr>
<tr>
<td>Anthony Bisulco</td>
<td>BS</td>
<td>NEU</td>
<td>5/2019</td>
</tr>
<tr>
<td>Luigi Annese</td>
<td>BS</td>
<td>NEU</td>
<td>5/2019</td>
</tr>
<tr>
<td>Alex Zhu</td>
<td>High School</td>
<td>Wayland High School</td>
<td>5/2019</td>
</tr>
<tr>
<td>Diego Cachay</td>
<td>High School</td>
<td>Boston Latin School</td>
<td>5/2019</td>
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II. PROJECT DESCRIPTION

A. Project Overview

As the problem of identifying suicide bombers wearing explosives concealed under clothing becomes increasingly important, it becomes essential to detect suspicious individuals at a distance. Systems which employ multiple sensors to determine the presence of explosives on people are being developed. Their functions include observing and following individuals with intelligent video, identifying explosives residues or heat signatures on the outer surface of their clothing, and characterizing explosives using penetrating X-rays [1, 2], terahertz waves [3-5], neutron analysis [6, 7], or nuclear quadrupole resonance (NQR) [8, 9]. At present, radar is the only modality that can both penetrate and sense beneath clothing at a distance of 2 to 50 meters without causing physical harm.

The objective of this project is the hardware development and evaluation of an inexpensive, high-resolution radar that can distinguish security threats hidden on individuals at mid-ranges (2-10 meters) using an “on-the-move” configuration, and at standoff-ranges (10-40 meters) using a “van-based” configuration (see Fig. 1 on the next page).
B. Biennial Review Results and Related Actions to Address

The reviewers identified several strengths for this project. Among them are the following: 1) rapid adaptation of the first generation (Gen-1) of the imaging system and algorithm development for the other generation systems; and 2) quantitative performance evaluation of the imaging system for both synthetic and experimental data.

The reviewers identified the following weaknesses of this project: 1) the need to identify the sequence of tasks that will be followed to reach a successful conclusion; 2) the need to study non-uniform fast Fourier transform (FFT); and 3) the need to define the transition timelines/plans.

In Year 4, we addressed the first weaknesses as follows: 1) We worked on the Alternating Direction Method of Multipliers (ADMM)-based compressive imaging for the data collected by the second generation (Gen-2) system. In Year 5, we will address the second and third weaknesses as follows; 2) We will study the extension of the FFT to 3D, including the non-uniform FFT; and 3) We will schedule a transition plan with our industry partner HXI and the ALERT Transition Team.
C. State of the Art and Technical Approach

The outcome of this project would be the first inexpensive, high-resolution radar system with a special application to detect and identify potential suicide bombers. Its uniqueness is based on the ability to work on multistatic configurations, in which the information from multiple receivers and transmitters are coherently combined by using a common local oscillator. This project has the potential to be the first radar system that is capable of functioning at multiple ranges for both indoor and outdoor scenarios. An analysis of the state of the art is incorporated into Section II.D.

Table 1 shows the algorithmic development road map, including the steps needed to go from a 3D mechanical scanning imaging system (Gen-1 [10]) to a 3D fully electronic scanning imaging system (Generation 3, Gen-3 [11,12]). An intermediate imaging system (Gen-2), capable of imaging small targets in a fully electronic fashion and large targets in a hybrid electrical/mechanical fashion, will be used for a smooth transition between the Gen-1 and Gen-3 imaging systems.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Generation 1 – Sparse Array of Receivers</th>
<th>Generation 2 – Sparse Array of Transmitters and Receivers</th>
<th>Generation 3 – Sparse Array and Compressive Reflector Antenna</th>
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<tbody>
<tr>
<td>SAR imaging/ pseudo-inverse</td>
<td>Task-1.1: 100% Completed</td>
<td>Non Applicable</td>
<td>Non Applicable</td>
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<tr>
<td></td>
<td>- 3D Validated with synthetic data</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- 3D Validated with experimental data</td>
<td></td>
<td></td>
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<tr>
<td>FFT imaging/ multistatic</td>
<td>Task-1.2: 100% Completed</td>
<td>Non Applicable</td>
<td>Non Applicable</td>
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<tr>
<td></td>
<td>- 3D Validated with synthetic data</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>- 3D Validated with experimental data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CS imaging/ Nesterov-Based</td>
<td>Task-1.3: 100% Completed</td>
<td>Task-2.3: (Y3: 75%, Y4:75%)</td>
<td>Task-3.3: (Y3: 25%, Y4:80%)</td>
</tr>
<tr>
<td></td>
<td>- 3D Validated with synthetic data</td>
<td>- 3D Validated with synthetic data</td>
<td>- 3D Validated with synthetic data and point-like scatter</td>
</tr>
<tr>
<td></td>
<td>- 3D Validated with experimental data</td>
<td>- Pending; 3D Validated with experimental data</td>
<td>- Pending; 3D Validated with experimental data</td>
</tr>
<tr>
<td>CS imaging/ ADMM</td>
<td>Non Applicable</td>
<td>Task-2.4: (Y3: 75%, Y4:95%)</td>
<td>Task-3.4: (Y3: 25%, Y4:75%)</td>
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<tr>
<td></td>
<td></td>
<td>- 3D Validated with synthetic data and point-like scatter</td>
<td>- 3D Validated with synthetic data and point-like scatter</td>
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<td></td>
<td>- Pending; 3D Validated with experimental data</td>
<td>- Pending; 3D Validated with experimental data</td>
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<td>CS-High Capacity Sensing Design</td>
<td>Non Applicable</td>
<td>Non Applicable</td>
<td>Task-3.5: (Y3: 25%, Y4:50%)</td>
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<td></td>
<td></td>
<td></td>
<td>- 3D design</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>- Pending; 3D design and experimental validation</td>
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<tr>
<td>New CS Imaging Algorithms</td>
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<td>Task-2.6: (Y3: 0%, Y4:25%)</td>
<td>Task-3.6: 0% Completed</td>
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<tr>
<td></td>
<td></td>
<td>- Pending; 3D Validation with synthetic and experimental data</td>
<td></td>
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Table 1: Algorithmic development roadmap towards a fully electronic radar imaging system: from Gen-1 [10] to Gen-3 [11,12].

The following activities were developed for this project: 1) ADMM-based Compressive Imaging using synthetic and experimental data of the Gen-2 system and a potential Gen-3 system configuration (Task 2.4 and 3.4); 2) new Compressive Imaging Algorithms using synthetic data (Task 2.6); and 3) design of a high-capacity sensing system for Compressive Sensing (CS) imaging applications (Task 3.5). This project is intimately related to ALERT Project R3-B.1, “Hardware design for ‘Stand-off’ and ‘On-the-Move’ Detection of Security
Threats,” because it develops the imaging algorithms for the R3-B.1 hardware system. Additionally, many of the
technologies and techniques developed for this project are commonly used in near-field applications by
other ALERT projects, including Projects R3-A.2 and R3-A.3.

D. Major Contributions

A summary of the Year 4 major contributions can be found in Table 2.

<table>
<thead>
<tr>
<th>C.1 - ADMM-based Compressive Imaging (Tasks 2.4 and 3.4):</th>
<th>This year the main outcomes of this task have been the following:</th>
</tr>
</thead>
<tbody>
<tr>
<td>o Outcome 1.1 – ADMM-based Compressive Imaging using joint Norm-1 and Norm-2 regularization.</td>
<td></td>
</tr>
<tr>
<td>o Outcome 1.2 – ADMM-based Compressive Imaging using rows and columns division of the sensing matrix.</td>
<td></td>
</tr>
<tr>
<td>o Outcome 1.3 – Preliminary results of the ADMM-based Compressive Imaging algorithm</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>C.2 – New Compressive Imaging Algorithms (Tasks 2.6):</th>
</tr>
</thead>
<tbody>
<tr>
<td>o Outcome 2.1 – Physicality Constrained Compressive Sensing</td>
</tr>
<tr>
<td>o Outcome 2.2 - Sensing Matrix Design via Mutual Coherence Minimization for Electromagnetic Compressive Imaging Applications</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C.3 - Design of a high-capacity sensing system for Compressive Sensing imaging applications (Task 3.5):</th>
</tr>
</thead>
<tbody>
<tr>
<td>This year the main outcome of this task has been the following:</td>
</tr>
<tr>
<td>o Outcome 3.1 – Design of a compressive reflector for enhancing the sensing capacity.</td>
</tr>
<tr>
<td>o Outcome 3.2 - Compressive Imaging of extended human-size regions using an array of CRAs</td>
</tr>
</tbody>
</table>

Table 2: Summary of this year’s major contributions.

E. Milestones

E.1. ADMM-based Compressive Imaging (Tasks 2.4 and 3.4)

This year, we have continued our research on our ADMM-based CS algorithm that enables 3D imaging of security threats in a distributed fashion. Specifically, this year we have extended our ADMM method in order to allow a joint inversion using a combined Norm-1 and Norm-2 regularization in a fully parallelizable fashion, thus enabling quasi real-time imaging. Moreover, we have developed a new mathematical formulation that will enable to solve the problem after breaking the sensing matrix by rows, by columns, or both, in order execute the inversion in an even more distributed fashion. These efforts are described in the next section.

E.1.a. ADMM-based Compressive Imaging using joint Norm-1 and Norm-2 regularization

The alternating direction method of multipliers (ADMM) has been presented in previous works with a Norm-1 regularization. It can be extended to other regularizations. Here we present a newly developed capability that enables our ADMM algorithm to use joint Norm-1 and Norm-2 regularizations. Specifically, the new algorithm uses a linear combination of both regularizations in the consensus distributed fashion, as it can be seen next.

Given the linear problem

\[ \mathbf{g} = \mathbf{H} \cdot \mathbf{u} + \mathbf{w} \quad (1) \]

where \( \mathbf{g} \in \mathbb{C}^{N_m} \) is the vector of measurements, \( \mathbf{H} \in \mathbb{C}^{N_m \times N_p} \) is the sensing matrix, \( \mathbf{w} \in \mathbb{C}^{N_m} \) represents the noise collected by the receiver, and \( \mathbf{u} \in \mathbb{C}^{N_p} \) is the unknown complex vector; the Norm-1 and Norm-2
A regularization consensus ADMM problem is defined as follows:

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2} \sum_{i=1}^{N} \|H_i u_i - g_i\|_2^2 + \alpha \frac{1}{2} \|v\|_2^2 + (1 - \alpha) \lambda \|v\|_1 \\
\text{s.t.} & \quad u_i - v = 0 \quad \forall i = 1, \ldots, N
\end{align*}
\]  

(2)

where \(H_i\) are row submatrices of the sensing matrix \(H\), and \(g_i\) are subvectors of the vector of measurements \(g\). The variables \(u_i\) are copies of the unknown vector \(u\), which are used for solving the problem for each \(H_i\) and \(g_i\). The constraint forces that all partial solutions agree through is the variable \(v\). The parameter \(\alpha\) is a weight value which varies between 0 (corresponding to Norm-1 regularization only) and 1 (corresponding to Norm-2 regularization only).

The Lagrangian function for this methodology is defined as follows:

\[
L(u_i, v, s_i) = \frac{1}{2} \sum_{i=1}^{N} \|H_i u_i - g_i\|_2^2 + \alpha \frac{1}{2} \|v\|_2^2 + (1 - \alpha) \lambda \|v\|_1 + \frac{\rho}{2} \sum_{i=1}^{N} \|u_i - v + s_i\|_2^2 - \frac{\rho}{2} \sum_{i=1}^{N} \|s_i\|_2^2,
\]

(3)

where \(s_i\) are the dual variables for each constraint.

This problem is solved by the iteration of the following solutions:

\[
u_i^{k+1} = (H_i^t H_i + \rho I)^{-1} (H_i^t g_i + \rho (v^k - s_i^k))
\]

(4)

\[
v^{k+1} = \frac{1}{1+ \frac{\rho M}{N \rho}} S^{(1-\alpha) \rho \lambda / \rho} (\tilde{u}^{k+1} + s^k)
\]

(5)

\[s_i^{k+1} = s_i^k + (u_i^{k+1} - v^{k+1})
\]

(6)

Notice that, for \(\alpha = 0\), the consensus variable \(v\) is the soft-thresholding of the averaging of \(u\) and \(s\), as expected for Norm-1 regularization; meanwhile for \(\alpha = 1\), the variable \(v\) is just the averaging of \(u\) and \(s\), as expected for Norm-2 regularization. A different value of \(\alpha\) will produce a weight combination of Norm-1 and Norm-2 regularizations. The 2-D balls of the combination of Norm-1 and Norm-2 for different values of the parameter \(\alpha\) are shown in Figure 2 (on the next page).

**E.1.b. ADMM-based Compressive Imaging using rows and columns division of the sensing matrix**

Up until now, we have performed the consensus-based ADMM dividing the sensing matrix into rows, but it can be extended to the matrix division into rows and columns. It is important to note that for a given problem this scheme enables the user to solve even smaller problems in a more distributed fashion. Considering the same problem as in (1), let us divide the sensing matrix into \(M\) sub-rows and \(N\) sub-columns, as shown in Figure 3 (on the next page).

The problem to solve is now of the following form:

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2} \sum_{i=1}^{M} \sum_{j=1}^{N} \|H_{ij} u_{ij} - g_{ij}\|_2^2 + \lambda \|v_j\|_1 \\
\text{s.t.} & \quad u_{ij} - v_j = 0 \quad \forall i = 1, \ldots, M, \forall j = 1, \ldots, N
\end{align*}
\]

(7)

where \(u_{ij}\) is the i-th replic of the j-th sub-vector of the unknown vector \(u\). The Lagrangian function is the following:

\[
L(u_{ij}, v_j, s_j) = \frac{1}{2} \sum_{i=1}^{M} \sum_{j=1}^{N} \|H_{ij} u_{ij} - g_{ij}\|_2^2 + \lambda \|v_j\|_1 + \frac{\rho}{2} \sum_{i=1}^{M} \sum_{j=1}^{N} \|u_{ij} - v_j + s_j\|_2^2 - \frac{\rho}{2} \sum_{i=1}^{M} \sum_{j=1}^{N} \|s_j\|_2^2,
\]

(8)
where $s^i_j$ are the dual variables for each constraint.

The solution of this optimization problem is given by the following iterative solutions:

$$
u^{p,k+1}_q = \left( H_{pq} H_{pq} + \rho I \right)^{-1} \left( H_{pq} \left( g_p - \sum_{j=1,j\neq q}^N H_{pq} u^{p,k}_j \right) + \rho \left( v^{k}_q - s^{p,k}_q \right) \right)$$  \hspace{1cm} (9)

$$v^{k+1}_q = S_{\lambda/M\rho} \left( \bar{u}^{k+1}_q + s^k_q \right)$$  \hspace{1cm} (10)

$$s^{p,k+1}_q = s^{p,k}_q + (u^{p,k+1}_q - v^{k+1}_q)$$  \hspace{1cm} (11)

Figure 2: 2-D balls of the combination of Norm-1 and Norm-2 for different values of the parameter $\alpha$.

Figure 3: Representation of the division of the sensing matrix by rows and by columns.
E.1.c. Preliminary results of the ADMM-based Compressive Imaging algorithm

In order to test the algorithms presented above, a random matrix $H \in \mathbb{R}^{50\times100}$ has been generated with Gaussian values. A known vector $u \in \mathbb{R}^{100}$ is considered as a reference. The measurements vector $g \in \mathbb{C}^{50}$ is obtained by the multiplication $g = H \cdot u$. In the following examples, the final solution is compared to the reference one. Moreover, the primal $r^k$ and dual $d^k$ residual errors are also presented; these errors are given by the following expressions:

$$
\|r^k\|_2^2 = \sum_{i=1}^{M} \sum_{j=1}^{N} |u_{ij}^k - v_{ij}^k|^2 \\
\|d^k\|_2^2 = M \rho^2 \sum_{j=1}^{N} |s_{j}^k - s_{j}^{k-1}|^2
$$

(12) \hspace{1cm} (13)

**Example #1:** In this example, $u$ is set to be a sparse vector with 90% entries equal to 0. As expected, the reconstruction with Norm-1 regularization tries to find the sparsest solution. As shown in Figure 4, the algorithm is capable of recovering the actual solution with a high fidelity in less than 150 iterations.

![Figure 4: Reconstruction of a sparse vector with ADMM using Norm-1 regularization.](image)

**Example #2:** In this example, the ADMM is executed using Norm-2 regularization. This configuration of the algorithm searches for the solution with lower energy. In the next three cases, we consider a square sensing matrix $H \in \mathbb{R}^{100\times100}$. As it is shown in Figure 5, the algorithm is capable of recovering the original signal with high fidelity in only 150 iterations.

![Figure 5: Reconstruction of a sparse vector with ADMM Norm-2 regularization.](image)
**Example #3:** In this example, the vector $\mathbf{u}$ is non-sparse, and $\mathbf{H} \in \mathbb{C}^{100 \times 100}$. As it is shown in Figure 6, the ADMM with Norm-1 regularization, which searches for the sparsest solution, provides a good reconstruction.

![Figure 6: Reconstruction of a non-sparse vector with ADMM Norm-1 regularization.](image1)

**Example #4:** In this example, the vector $\mathbf{u}$ is still non-sparse, and $\mathbf{H} \in \mathbb{R}^{100 \times 100}$. As it can be seen in Figure 7, the ADMM with Norm-2 regularization, which finds the solution with minimum energy, provides a good reconstruction.

![Figure 7: Reconstruction of a non-sparse vector with ADMM Norm-2 regularization.](image2)

**Example #5:** At first glance, after looking at the results in the last two examples, it is not clear which regularization technique—Norm-1, Norm-2, or even a linear combination of them—may lead to the best reconstruction. The following example investigates this concept by specifically applying the ADMM algorithm to different linear combinations of the Norm-1 and Norm-2 regularizers for different sparsity levels. With an underdetermined sensing matrix $\mathbf{H} \in \mathbb{R}^{75 \times 100}$, which implies recovering vectors of 100 elements with 75 measurements, the compressive sensing criteria for real signals states that the maximum sparsity level that the vector $\mathbf{u}$ could have when using Norm-1 regularizers is less than $75/2 \approx 37.5$. For higher sparsity levels, more than 37.5 non-zeros, compressive sensing techniques using Norm-1 regularizers do not ensure the reconstruction of the original signal; so, for these cases, using a linear combination of the Norm-1 and Norm-2 regularization may lead to a better solution.

An analysis for different sparsity levels has been conducted, in order to find the best combination between...
Norm-1 and Norm-2 that leads to a minimum quadratic error of the reconstructed signal. The parameters of $\alpha$, $\lambda$ and $\mu$ are optimized according to Equation (2). The results are presented in Figure 8 and Table 3. It is clear to see that, as expected, for low sparsity levels less than 40, the Norm-1 is predominant. However, when the number of non-zero elements increase, a linear combination of the two norm leads to the best result. In the extreme case, in which the number of non-zero elements is 100, the best result is achieved when the weight of the Norm-1 regularizer is one fourth of that of the Norm-2 regularizer.

Figure 8: Reconstruction for different sparsity levels. Original (blue), reconstructed (red). The error indicates the Norm-2 of the difference between the original and the reconstructed vectors.

<table>
<thead>
<tr>
<th>Sparsity level</th>
<th>$\alpha$</th>
<th>$\lambda$</th>
<th>$\mu$</th>
<th>$|x - \tilde{x}|_2$</th>
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<tbody>
<tr>
<td>10</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
<td>0.0036</td>
</tr>
<tr>
<td>20</td>
<td>0.0</td>
<td>0.1</td>
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<tr>
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<td>0.1</td>
<td>0.0177</td>
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<tr>
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<td>0.1</td>
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</tr>
<tr>
<td>50</td>
<td>0.2</td>
<td>0.1</td>
<td>0.1</td>
<td>2.2759</td>
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<tr>
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<td>0.1</td>
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<td>0.1</td>
<td>4.6084</td>
</tr>
<tr>
<td>90</td>
<td>0.6</td>
<td>0.1</td>
<td>0.1</td>
<td>4.8094</td>
</tr>
<tr>
<td>100</td>
<td>0.8</td>
<td>0.1</td>
<td>0.1</td>
<td>5.2945</td>
</tr>
</tbody>
</table>

Table 3: Numerical values of the optimal parameters for the analysis of different levels of sparsity.
Example #6: The Norm-1 regularized ADMM algorithm has been tested for sparse signals when the sensing matrix is divided by rows, by columns, and by both rows and columns. Note that solving the problem in this distributed fashion will be very important for quasi-real time imaging applications. The sensing matrix is created using random Gaussian entries, $\mathbf{H} \in \mathbb{R}^{50 \times 100}$.

The results when the sensing matrix is divided into 5 rows, 4 columns, and 5 rows and 2 columns are presented in Figure 9 (on the next page). When the sensing matrix is divided only into columns, the convergence is slower than when it is only divided into rows, as can be noticed when comparing the dual residual convergence of Figure 9a and Figure 9b. Finally, when dividing the sensing matrix by rows and columns at the same time, the algorithm converges obtaining a solution very close to the original one, as shown in Figure 9c. These simple examples show that our Norm-1 regularized ADMM algorithm works for sensing matrices that are divided into rows and columns.
Figure 9: Reconstruction of a sparse vector with ADMM Norm-1 regularization when the sensing matrix is divided into (a) 5 rows, (b) 4 columns, and (c) 5 rows and 2 columns.
E.2. **New Compressive Sensing and Imaging algorithms (Task 2.6).**

This year we have worked on new Compressive Sensing and Imaging algorithms that have the potential to perform imaging with a reduced number of measurements and hardware components. This work is summarized next.

E.2.a. **Physicality Constrained Compressive Sensing**

This year, we have also developed a new Physicality Constrained Compressive Sensing algorithm. In electromagnetic imaging applications, one attempts to reconstruct the constitutive parameters or reflectivity profile of an object of interest from a set of scattered electric field measurements. Reconstruction accuracy is largely dependent upon the fidelity of the measurements, that is, the total number of measurements and their degree of independence. When classical imaging algorithms are employed, the reconstruction accuracy can be improved by increasing the number of measurements, for example by recording measurements at more locations or by exciting the object of interest using more frequencies. If performed naively, however, this approach can be expensive, both in terms of the hardware complexity of the imaging system and in terms of the information efficiency of each measurement. As more measurements are added to the system, the amount of additional information obtained by each new measurement can decrease dramatically.

Compressive Sensing (CS) is a novel signal processing paradigm, which states that sparse signals can be recovered from a small number of linear measurements by solving a convex and computationally tractable $\ell_1$-norm (Norm-1) minimization problem. Accurate recovery is only guaranteed when the sensing matrix is "well-behaved" according to a set of performance measures that relate the independence of the columns of the sensing matrix. Many electromagnetic imaging applications can be linearized using the Born approximation, wherein the unknown vector $x \in \mathbb{C}^N$ is the contrast variable. The contrast variable is related to the unknown complex permittivity $\epsilon$ of the scatterers and the known complex permittivity $\epsilon_b$ of the background medium according to the relationship $x = \text{diag}(\epsilon_b)^{-1}(\epsilon - \epsilon_b)$. When the contrast variable is known to be sparse, standard CS techniques have been shown to be successful. However, these techniques are sub-optimal because they do not consider the fundamental constraints placed on the permittivity by the laws of physics.

Instead of using standard CS techniques, in [13], we proposed the use of the following Physicality Constrained Compressive Sensing (PCCS) optimization program:

$$\begin{align*}
\text{minimize} & \quad ||x||_{\ell_1} \\
\text{subject to} & \quad ||Ax - y||_{\ell_2} \leq \eta \\
& \quad Re(\text{diag}(\epsilon_b)\epsilon + \epsilon_b) \geq 1 \\
& \quad Im(\text{diag}(\epsilon_b)\epsilon + \epsilon_b) \geq 0
\end{align*}$$

Unlike the standard CS problems, the PCCS optimization program requires the solution vector to be physically realizable. Intuitively, one expects that the PCCS program will generate more accurate solutions than the standard CS program. To demonstrate this, consider the images displayed in Figure 10 (on the next page). These images consider a two-dimensional imaging problem in which the measurements are noiseless ($\eta = 0$) and the background medium is freespce ($\epsilon_b = 1$, so that the physicality constraints reduce to $Re(x) \geq 0$ and $Im(x) \geq 0$). In both figures, the blue line represents the set of solutions that match the measured data, the green box represents the solutions that satisfy the physicality constraints, and the red diamond represents the $\ell_1$-ball of a certain radius. The left image shows that the standard CS solution occurs at $x = (-1,0)^T$, $x = (0,1)^T$ which violates the physicality constraint. The right image, however, shows that the PCCS solution occurs at, which is the true sparse solution to the problem.
To demonstrate the effectiveness of PCCS even further, we performed a numerical analysis of the reconstruction accuracies of the traditional CS and PCCS problems in [13]. Figure 11 displays the reconstruction accuracies for the standard CS and PCCS problems for a sensing matrix $A \in \mathbb{C}^{48 \times 500}$. For small sparsity levels, both techniques performed equally well; however, for sparsity levels greater than 10, the PCCS program clearly outperformed the standard CS program.

**E.2.b. Sensing Matrix Design via Mutual Coherence Minimization for Electromagnetic Compressive Imaging Applications (Task 2.6)**

It is well known that the success of Compressive Sensing (CS) technique largely depends upon properties of the sensing matrix $A$. The Restricted Isometry Property (RIP) is the most commonly used performance metric for assessing the CS recovery capabilities of a sensing matrix because it provides the most powerful bounds on the reconstruction performance. One drawback of the RIP is that it is extremely difficult to verify for deterministic matrices. To get around this issue, researchers resort to generating sensing matrices whose
elements are drawn from independent and identically distributed sub-Gaussian random variables. Random sensing matrices of this form have been shown to satisfy the RIP with overwhelming probability. Unfortunately, random matrices cannot be utilized in many real-world applications, such as electromagnetic imaging applications.

In our recent paper [14], we introduced a sensing matrix design method based on the mutual coherence. Although the mutual coherence provides weaker reconstruction guarantees than the RIP, it is a more practical metric for deterministic matrices. Formally, the coherence of a sensing matrix is defined as follows:

\[ \mu(A) = \max_{1 \leq i \neq j \leq N} \frac{|a_i^T a_j|}{\|a_i\|_2 \|a_j\|_2} \]

where \( a_i \) is the i-th column of the sensing matrix. Unlike the RIP, which requires an exponentially increasing number of computations, the coherence can be computed using only \( N(N - 1)/2 \) vector inner products.

In the coherence minimization design method, the sensing matrix \( A \in \mathbb{C}^{M \times N} \) is assumed to be a function of design variables \( p \in \mathbb{C}^k \) according to the possibly nonlinear, but differentiable relationship \( A = f(p) \). The design algorithm then seeks the minimizer for the following optimization program:

\[
\begin{align*}
\text{maximize} & \quad \mu(A) \\
\text{subject to} & \quad A = f(p) \\
& \quad p \in Q_p
\end{align*}
\]

where \( Q_p \) defines the feasible set of values that \( p \) can take. This is a nonlinear, non-convex problem, which can be solved using the Augmented Lagrangian method after some refactoring.

A numerical analysis was performed [14] in order to assess the capabilities of the coherence design method. Consider an imaging system in which a single transmitting and receiving antenna is used to excite a region of interest with a single frequency. This antenna was constrained to operate at 64 positions within a \( 5\lambda \times 5\lambda \) grid located a distance of \( 5\lambda \) away from the imaging region. The objective of the design problem was to select the locations that the antenna would operate at Figure 12 (on the next page) displays the locations that the antenna operated at for the baseline design (blue) and the optimized design (red). While the sensing matrix for the baseline design, which distributed the antenna positions uniformly, had a coherence of 0.8300, the optimized design had a coherence of 0.2252. Intuitively, one would expect the optimized design to provide better CS reconstruction performance than the baseline design. This result is confirmed by Figure 13 (on the next page), which displays the reconstruction accuracies of the baseline design (blue), optimized design (red), and a random design (green) for reference when Orthogonal Matching Pursuit (OMP) is used as the reconstruction algorithm.
E.3. Design of high-capacity sensing system for CS imaging applications (Task 3.5)

E.3.a. Design of a compressive reflector for enhancing the sensing capacity

This year, we have studied a new Compressive Reflector Antenna (CRA), based on digitized Metamaterial Absorbers (MMAs), as a mechanism to enhance the sensing capacity of mm-wave imaging systems. The sensing system, as shown in Figure 14 (on the next page), is composed of a specially tailored compressive reflector antenna fed by a 2D array of conical horns. The conical horns are configured in a cross shape along the focal plane of the reflector, and it is arranged as follows: $N_{\text{Tx}}$ transmitting and $N_{\text{Rx}}$ receiving elements are positioned equidistantly along the x-axis and y-axis, respectively. The feeding element parameters—including (but not limited to) the number of horns, spacing between them, and amplitude taper on the reflector’s edge—deeply impact the performance of the imaging system. Indeed, these parameters should be selected in a way that the effective aperture, obtained after convolving the transmitting and receiving arrays, is capable of imaging the whole region of interest.
The MMA-based CRA consists of a traditional parabolic reflector antenna, whose surface is covered with digitized MMAs (Figure 15 shows the front view of a 4-bit MMA aperture). Based on the ‘1’ or ‘0’ values associated with each digit of the binary number, the MMA may or may not absorb the incident electromagnetic power at different resonance frequencies, respectively. For example, in the 4-bit MMA design shown in Figure 15, the first, second, third, and fourth digits correspond to resonances at 71 GHz, 73 GHz, 75 GHz and 77 GHz, respectively. Simulations show that the bandwidth for the single resonance MMAs is about 1.56 GHz, corresponding to an approximate quality factor of 46.

Figure 14: Illustration of the proposed imaging setup. The feeding array located on the focal plane induces currents on the surface of the CRA, which ultimately creates the spectral codes in the imaging region. The spectral codes (magnitude of electric field) created by the CRA are shown as a function of frequency, while the CRA is illuminated by Tx₂.

Figure 15: Front view of the proposed CRA. The surface of the reflector is divided into 16 domains and each domain is coated with a unique 4-bit MMA.
A meander-line MMA has been designed (see Figure 16) to build the unit-cell of the digitized MMAs. The MMA unit-cell is simulated and designed using the commercial software HFSS. A general incident plane wave with an arbitrary elevation ($\theta$) and azimuth ($\phi$) angle is defined to excite the unit-cell (Figure 16b). The unit-cell benefits from two unique features: 1) It is almost insensitive to the polarization of the incident plane wave, i.e. for a given elevation incident angle ($\theta$ in Figure 16), the reflection coefficient is not significantly altered for different azimuth incident angles ($\phi$ in Figure 16); and 2) It has a near-unity absorption rate for wave excitations with normal incident angles, i.e. for the elevation incident angle of $\theta = 0$, the absorption rate value which is defined as $A = 1 - |S_{11}|^2 - |S_{21}|^2$, is near unity.

![Figure 16](image)

Figure 16: (a) Top view, and (b) 3-D view of the polarization-independent meander-line MMA unit cell. The dimensions in $\mu$m are: $a_x = a_y = 1300, l = 398, w = 43, g = 43.$

A set of simulations was performed demonstrating the aforementioned features of the MMA. Specifically, Figures 17a and Figure 17b (on the next page) illustrate the absorption rate and $|S_{11}|^2$ plots for TE and TM excitations, respectively. The plots are for a fixed value of elevation ($\theta = 30^\circ$) and different azimuth incident angles ($\phi = 0^\circ; 30^\circ; 60^\circ; and 90^\circ$). These figures show that only a small frequency shift of the resonant frequency (less than 0.3\%) is produced for different incident angles. Moreover, the peak at the resonant frequency is in all cases very close to unity (larger than 0.99). The absorption bandwidth, defined as the frequency range in which absorption is above one half of its maximum value, is 1.64 GHz.
Based on this MMA unit-cell design, a scaling factor has been used to obtain designs resonating at different frequencies. In this regard, MMAs with resonances at 73 GHz, 75 GHz, and 77 GHz were achieved by using a scaling factor of $S = 0.97$, $S = 0.95$, and $S = 0.93$, respectively. For the new designs, the periodicities of the unit-cell ($a_x$ and $a_y$) are kept the same and the scaling is applied only on the geometrical parameters of the meander-line pattern ($l$, $w$ and $g$). Figure 18 depicts the absorption rate and $|S_{11}|^2$ for the four MMA designs, which are excited by a TEM-mode plane wave.

Figure 17: Absorption rate (solid lines) and $|S_{11}|$ (dashed lines) of the polarization-independent MMA at various incident angles for the (a) TE, and (b) TM incidence.

Figure 18: Absorption rate (solid lines) and $|S_{11}|$ (dashed lines) of the MMAs with different scaling factors for the TEM excitation: (black) $S = 1.00$, (blue) $S = 0.97$, (red) $S = 0.95$, and (green) $S = 0.93$. 

---

**Figure 17:** Absorption rate (solid lines) and $|S_{11}|$ (dashed lines) of the polarization-independent MMA at various incident angles for the (a) TE, and (b) TM incidence.

**Figure 18:** Absorption rate (solid lines) and $|S_{11}|$ (dashed lines) of the MMAs with different scaling factors for the TEM excitation: (black) $S = 1.00$, (blue) $S = 0.97$, (red) $S = 0.95$, and (green) $S = 0.93$. 

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**Figure 17:**

- **Absorption rate (solid lines)**: Depicts the absorption rate of the MMA at various incident angles for the (a) TE, and (b) TM incidence.
- **$|S_{11}|$ (dashed lines)**: Shows the magnitude of the reflection coefficient $S_{11}$ against frequency for different incident angles.

**Figure 18:**

- **Absorption rate (solid lines)**: Illustrates the absorption rate for the MMAs with different scaling factors for the TEM excitation.
- **$|S_{11}|$ (dashed lines)**: Displays the magnitude of the reflection coefficient $S_{11}$ against frequency for various scaling factors.
In order to design a 4-bit MMA, the unit-cell design is extended to a 2×2 unit cell configuration, as illustrated in Figure 19a (on the next page). Each digit of the 4-bit MMA is associated with one of the four basic MMA unit-cell designs. Based on the ‘1’ or ‘0’ values associated with each digit of the 4-bit binary number, the MMA may or may not absorb the incident electromagnetic power at four different resonance frequencies, respectively. The scaling factor \( S \) for the first, second, third and fourth digits corresponds to resonances at 71GHz, 73GHz, 75GHz and 77GHz, respectively. Figures 19b through 19f illustrate the absorption rate as well as the magnitude and phase of \( S_{11} \) plots, for some examples of the presented 4-bit MMA. A TEM-mode plane wave is used to illuminate the MMA. It is apparent from the plots that there is some frequency shift in the peak value of the absorption rate, with respect to the expected resonance frequency. This is due to the mutual coupling between the adjacent digits. However, the scaling factors for each digit could be customized so that absorption rate peak can be tuned to be at the desired frequency. The volume loss density in the top layer for the ‘1111’ MMA is shown in Figure 19; it is excited with the TEM-mode plane wave for \( \varphi = 0^\circ \) (Figure 19b), \( \varphi = 45^\circ \) (Figure 19c), and \( \varphi = 90^\circ \) (Figure 16d). As illustrated in Figure 20b (on the following page), the electric field has only components in x-axis; and, therefore, only meander-lines with their long side aligned in y-axis will absorb the incident power. In Figure 20c, the electric field has components in both the x-axis and y-axis; hence, meander-lines having their long side aligned in x-axis and y-axis will both absorb the incident power. Finally, as expected, at each frequency only the MMA digit associated to that frequency absorbs the incident power.
Figure 19: Examples of absorption rate and $S_{ij}$ of the (a) 4-bit MMA unit cell with binary digits of (b) '0011', (c) '0101', (d) '0111', (e) '1001', and (f) '1111'. 
The performance of the 4-bit MMA-based CRA is evaluated in an active mm-wave imaging application. The physical and electrical parameters of the imaging system are described in Table 4 (on the next page). Our numerical solver (MECA), which is based on physical optics, was used for the simulations. The measurements were collected through a 7 GHz frequency span around a 73.5 GHz center frequency. The range distance between the focal plane of the CRA and the center of the imaging domain was 84 cm; and the aperture size $D$ in both x-axis and y-axis was 30 cm. The range and cross-range resolution of the imaging system is calculated to be $R_r = 21.4$ mm and $R_{cr} = 23$ mm, respectively. Accordingly, the imaging domain was discretized according to the proposed range and cross-range resolution.

Figure 20: Volume loss density on top layer of the 4-bit MMA unit cell with binary digit of ‘1111’ for the (a) TEM excitation with (b) $\varphi = 0^\circ$, (c) $\varphi = 45^\circ$, and (d) $\varphi = 90^\circ$.
The sensing matrix $H$ was calculated using our MECA solver. Figure 21a shows the improved singular value distribution of the CRA when compared to that of the Traditional Reflector Antenna (TRA), and Figure 21b shows how the sensing capacity of the CRA is enhanced when increasing the Signal to Noise Ratio (SNR). Figure 21b shows that there is an enhanced capacity when using the frequency-dependent MMAs to the imaging system. For example, if we assume an SNR level equal to 40 dB, the metamaterial-based reflector would have 97 more effective numbers of singular values (measurement codes) above the noise floor than the traditional reflector antenna. Ultimately, this would improve the sensing capacity of the MMA-based reflector, which can be inferred as an enhancement in the imaging performance.

<table>
<thead>
<tr>
<th>PARAMETER</th>
<th>VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency band</td>
<td>70-77 GHz</td>
</tr>
<tr>
<td>No. of frequencies ($N_f$)</td>
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</tr>
<tr>
<td>Reflector diameter ($D$)</td>
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</tr>
<tr>
<td>Focal length ($f$)</td>
<td>30 cm</td>
</tr>
<tr>
<td>No. of Tx.</td>
<td>4</td>
</tr>
<tr>
<td>No. of Rx.</td>
<td>4</td>
</tr>
<tr>
<td>Triangle size on the reflector</td>
<td>$5\lambda_{cr} = 4.1$ mm</td>
</tr>
<tr>
<td>Number of measurements (codes)</td>
<td>$N_T N_R N_{p_{eq}} = 240$</td>
</tr>
<tr>
<td>Number of pixels</td>
<td>$N_p = 80,000$</td>
</tr>
</tbody>
</table>

Table 4: Design parameters of the single CRA.

The sensing matrix $H$ was calculated using our MECA solver. Figure 21a shows the improved singular value distribution of the CRA when compared to that of the Traditional Reflector Antenna (TRA), and Figure 21b shows how the sensing capacity of the CRA is enhanced when increasing the Signal to Noise Ratio (SNR). Figure 21b shows that there is an enhanced capacity when using the frequency-dependent MMAs to the imaging system. For example, if we assume an SNR level equal to 40 dB, the metamaterial-based reflector would have 97 more effective numbers of singular values (measurement codes) above the noise floor than the traditional reflector antenna. Ultimately, this would improve the sensing capacity of the MMA-based reflector, which can be inferred as an enhancement in the imaging performance.

Figure 21: (a) Normalized singular value distribution and (b) sensing capacity comparison between the TRA and the 4-bit CRA.
By plotting the field patterns in the imaging region, one can study the codes as a function of frequency. Figure 22 shows the radiation pattern of the MMA-based reflector on the xy-plane at a distance $z = 85$ cm from the focal plane. These radiation patterns correspond to the case where Rx$_2$ is exciting the reflector, and they are plotted for 70.5 GHz (Figure 22a), 72.5 GHz (Figure 22b), 74.5 GHz (Figure 22c) and 76.5 GHz (Figure 22d). As expected, the radiation pattern for each one of the antennas is frequency dependent. This behavior is due to the dispersion of the 4-bit MMAs.

The resolution of the MMA-based reflector can be shown by plotting the Point Spread Function (PSF) of the system. This is shown in Figure 23 (on the next page) when the PSF is focused at ([0, 0, 85] cm and [5, 5, 85] cm). Figure 23a and Figure 23b shows the PSF of the receiver and transmitter array, respectively, and Figure 23c is showing product of the receiver and the transmitter array PSFs.
The performance of the imaging system is tested on a 3D region containing several 2D PEC targets (see Figure 24 on the next page). Specifically, the imaging region contains three vertically oriented rectangles, three horizontally oriented rectangles, one square, and one circle. The width and height of the rectangles are equal to 12 mm and 61 mm, respectively. The side of the square is 24 mm, and the circle has a diameter equal to 24 mm. The center of the imaging domain is considered to be 84 cm far from the focal plane of the reflector, and the PEC scatterers are located in four different range positions, separated by 21 mm. The iso-contours in Figure 20 represent the level of the reflectivity, and the triangular facets show the position and shape of the

Figure 23: Beam focusing at (left) \([x, y, z] = [0, 0, 85]\) cm, and (right) \([x, y, z] = [5, 5, 85]\) cm, by the (a) receiver array, (b) transmitter array, and (c) product of the receiver and the transmitter array BFs.

The performance of the imaging system is tested on a 3D region containing several 2D PEC targets (see Figure 24 on the next page). Specifically, the imaging region contains three vertically oriented rectangles, three horizontally oriented rectangles, one square, and one circle. The width and height of the rectangles are equal to 12 mm and 61 mm, respectively. The side of the square is 24 mm, and the circle has a diameter equal to 24 mm. The center of the imaging domain is considered to be 84 cm far from the focal plane of the reflector, and the PEC scatterers are located in four different range positions, separated by 21 mm. The iso-contours in Figure 20 represent the level of the reflectivity, and the triangular facets show the position and shape of the
targets. The reconstruction for imaging using the traditional reflector antenna and the MMA-based reflector antenna are shown in Figure 24a and Figure 24b, respectively. The imaging has been carried out using the aforementioned Norm-1 regularized ADMM algorithm, for both the traditional and the MMA-based reflector. It is evident that the performance of the MMA-based reflector is superior to that of the traditional reflector.

![Figure 24](image)

**Figure 24:** Reconstructed image using ADMM iterative method for (a) the TRA and (b) the 4-bit CRA.

### E.3.b. Compressive Imaging of extended human-size regions using an array of CRAs.

As the last example of the high-capacity sensing systems, a CRA-based array made of six compressive reflectors is designed, in order to be able to image an extended human-size region. As depicted in Figure 25 (on the next page), the CRA is manufactured by introducing a set of discrete applique scatterers on the surface of a TRA. Each CRA is illuminated with two orthogonal transmitting and receiving arrays located on the focal plane. The electromagnetic cross-coupling between adjacent CRAs is used in order to enhance the sensing capacity of the system, as well as to extend the region that it can image. The proposed millimeter-wave sensing and imaging system is composed of six CRAs positioned in a cross configuration, as shown in Figure 26a (on the page following the next). The design parameters for each one of the reflectors are shown in Table 5 (on the next page). Both the vertical receiving array and the horizontal transmitting array of each CRA consists of 18 uniformly distributed conical horn antennas as shown in Figure 26b. The radar operates in the 70-77 GHz frequency band and only 10 frequencies are used to perform the imaging. Each CRA is designed to effectively be able to image over a projected circular area of 40 cm diameter in cross range (see red solid circles in Figure 26a) when the target is located 90 cm away from the focal plane. It is important to note that additional shaping techniques could be used in order to image over a wider projected cross range region. The CRA has an aperture size of 50 cm, and, as a result, none of the two adjacent CRAs will be able to image the region located between their two circular projections (see dashed green solid circle in Figure 26a). This drawback can be easily solved by coupling the information coming from the adjacent reflectors in a multi-static fashion, as illustrated by two green dashed arrows in Figure 26a. Given the aforementioned location of the target, this work only considered the electromagnetic cross-coupling between CRA-l and CRA-k: (l = 1; k = 2), (l = 1; k = 3), (l = 1; k = 4), (l = 2; k = 5), and (l = 5; k = 6).
Table 5: Design parameters for a single CRA.

<table>
<thead>
<tr>
<th>PARAMETER</th>
<th>PARAMETER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency band</td>
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</tr>
<tr>
<td>No. of frequencies ($N_f$)</td>
<td>10</td>
</tr>
<tr>
<td>Reflector Diameter ($D$)</td>
<td>50[cm]</td>
</tr>
<tr>
<td>Focal length ($f$)</td>
<td>50[cm]</td>
</tr>
<tr>
<td>Range ($z_0^1$)</td>
<td>90[cm]</td>
</tr>
<tr>
<td>No. of Tx.</td>
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</tr>
<tr>
<td>No. of Rx.</td>
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<tr>
<td>$&lt;D^e_x&gt;=&lt;D^e_y&gt;$</td>
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</tr>
<tr>
<td>$D^e_z$</td>
<td>Uniform(-10.5, +10.5) [mm]</td>
</tr>
</tbody>
</table>

Figure 25: 2D cross-section of a Traditional Reflector Antenna ($x > 0$) and Compressive Reflector Antenna ($x < 0$).
The target used in the simulation is a tessellated model of a human body. In this work, the 3D human model was projected onto a 2D plane located 90 cm away from the focal plane, and its extension to 3D will be a future line of investigation. Figure 27a shows the improved singular value distribution of a single CRA when compared to that of a TRA and Figure 27b shows how the sensing capacity of the CRA is enhanced for different Signal to Noise Ratios (SNRs). Finally, Figure 28 (on the next page) demonstrates that the proposed imaging system is capable of accurately reconstructing the target under investigation.

Figure 26: (a) 3D view of the proposed millimeter-wave sensing system composed of six CRAs and (b) induced currents on a CRA excited by Tx1. The feeding transmitter (red) and receiver (blue) arrays are located on the focal plane of the reflector.

The target used in the simulation is a tessellated model of a human body. In this work, the 3D human model was projected onto a 2D plane located 90 cm away from the focal plane, and its extension to 3D will be a future line of investigation. Figure 27a shows the improved singular value distribution of a single CRA when compared to that of a TRA and Figure 27b shows how the sensing capacity of the CRA is enhanced for different Signal to Noise Ratios (SNRs). Finally, Figure 28 (on the next page) demonstrates that the proposed imaging system is capable of accurately reconstructing the target under investigation.
F. **Future Plans**

- **ADMM-based Compressive Imaging** - For the next few years, the follow-on tasks and expected outcomes are the following:
  - Tasks 2.4 (Year 5) – Test and validate the algorithm in the Gen-2 system. Develop a Total Variation algorithm to exploit the sparsity of the image. The expected outcomes are a) validation of the algorithm in 3D with synthetic and experimental data in the fully electronic (Mode-E) Gen-2 system; and b) validation of a novel Total Variation algorithm.
  - Task 3.4 (Year 5 and beyond) – Test and validate the algorithm in the Gen-3 system. The expected outcomes are a) validation of the algorithm in 2D with synthetic and experimental data; and b) validation of the algorithm in 3D with synthetic and experimental data.

- **Design of a high-capacity sensing system for CS imaging applications**. For the next few years, the follow-on task and expected outcome are the following:
  - Task 3.5 (Years 5, and beyond) – Extend the design of the high-capacity sensing compressive reflector to 3D. The expected outcome is the design and experimental validation of a 3D Gen-3 system presenting maximum sensing capacity.

- **Accelerating Compressive Imaging using multistatic FFT** (including non-uniform FFT). For the next few years, the follow-on tasks and expected outcomes are the following:
  - Task 2.6 (Year 5 and beyond) – Test and validate the algorithm in the Gen-2 system. The expected outcomes are a) validation of the algorithm in 2D with synthetic and experimental data; and b) validation of the algorithm in 3D with synthetic and experimental data.
  - Task 3.6 (Year 5 and beyond) – Test and validate the algorithm in the Gen-3 system. The expected outcome is the validation of the algorithm in 3D with experimental data.

III. **RELEVANCE AND TRANSITION**

A. *Relevance of Research to the DHS Enterprise*
The following features will be of special relevance to the Department of Homeland Security (DHS) enterprise:

- Non-invasive, minimally disruptive “On-the-Move” scanning with quality imaging and high throughput; fast data collection in less than 10ms.
- Full body imaging with interrupted forward movement during mm-wave pedestrian surveillance; in multi-view.
- A small number of non-uniform sparse array of Tx/Rx radar modules will minimize the cost of on-the-move; five transmitters + five receivers + 10 switches.

B. Potential for Transition

The features of “On-the-Move” have attracted the attention of several industrial and government organizations.

- Target government customers: Transportation Security Administration (TSA), the U.S. Department of Justice (DOJ), Customs and Border Protection (CBP), and the Department of State.

C. Data and/or IP Acquisition Strategy

The hardware and algorithmic design, integration, and validation performed under this project will continue to generate IP. In the past, several provisional patents have been submitted to Northeastern University’s (NEU) IP office, and our connection with different transition partners will facilitate its transition into industry. Moreover, the hardware will also be used to create benchmark datasets that may be used by industry stakeholders in order to assess the performance of their reconstruction/imaging algorithms. Moreover, a new patent was awarded this year based on the work partially done in this project: U.S. Patent 9,575,045, “Signal Processing Methods and Systems for Explosives Detection and Identification Using Electromagnetic Radiation.”

D. Transition Pathway

HXI Inc. has been collaborating with our research team in the R3-B.2 project. Together, HXI and ALERT have designed, fabricated, integrated, and validated the radar system. We expect that after the assembling the first Gen-3 prototype, HXI will license our IP and transition the technology to the mm-wave imaging market. Additionally, new low-cost miniaturized modules are being developed by HXI for the next generation mm-wave system; some of these components will be tested by the Project R3-B.2 PI.

The PI has also established a working relationship with Smiths Detection and L3 Communications, which bodes well for future collaboration and transition.

E. Customer Connections

Customer Names & Program Offices:
- HXI – Mr. Earle Stewart
- Smith’s Detection Systems – Dr. Kris Roe
- L3 Communications – Dr. Simon Pongratz

Frequency of Contact & Level of Involvement in Project:
- The PI has weekly meetings with HXI for the project.
- The companies Smith’s Detection and L3 Communications had 3 to 4 meetings with the PI last year.
New proposals related to the topic of this research will be submitted to other federal funding agencies.

IV. PROJECT ACCOMPLISHMENTS AND DOCUMENTATION

A. Education and Workforce Development Activities

1. Course, Seminar, and/or Workshop Development

2. Student Internship, Job, and/or Research Opportunities
   a. Graduate students, Ali Molaei, Galia Ghazi, Luis Tirado, and Chang Liu play an important role in our research project. They will continue to assist in development of new hardware design and integration for the mm-wave radar system.
   b. Our undergraduate students, Anthony Bisulco and Luigi Annese, will continue to work on Projects R3-B.1 and R3-B.2. They will continue to be pillars of this project.

3. Interactions and Outreach to K-12, Community College, and/or Minority Serving Institution Students or Faculty
   a. The PI participated in the Building Bridges Program, which provides opportunities for high school students to visit NU’s laboratories and gain hands-on research experience in order to engage them in STEM education.
   b. The PI participated in the Young Scholars Program at Northeastern University, in which two high school students spent 6 weeks in Prof. Martinez’s lab learning about sensing and imaging.

4. Other Outcomes that Relate to Educational Improvement or Workforce Development
   a. Populating the research group with undergraduates brings homeland security technologies to undergraduate engineering students, and establishes a pipeline to train and provide a rich pool of talented new graduate student researchers.

B. Peer Reviewed Journal Articles


Pending-

C. Peer Reviewed Conference Proceedings

D. Other Presentations
1. Seminars
   a. Martinez-Lorenzo, J.A. "Mm-wave Imaging." NU Meeting with Analogic, Northeastern University, Boston, MA, 14 September 2016.
2. Poster Sessions
3. Interviews and/or News Articles
V. REFERENCES


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