Compressive Sensing of Earth Observations

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Compressive Sensing–Based High-Resolution Imaging and Tracking of Targets and Human Vital Sign Detection behind Walls

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Compressive Sensing–Based High-Resolution Imaging and Tracking of Targets and Human Vital Sign Detection behind Walls

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3.1 Introduction

The high-resolution and noninvasive imaging of stationary and moving human and its vital signatures through clutter, such as visually opaque obstacles (e.g. walls, doors, ground) has sparked a growing interest in through-the-wall radar imaging (TWRI) and ground-penetrating radar (GPR) in both military and civilian applications, such as homeland security, urban counterterrorism, search and rescue missions, and monitoring of the sick and elderly [1,2]. In many TWRI situations, exterior and/or interior building walls induce shadowing effects, which may result in image degradation, errors in geolocation, or complete masking of targets within the building. All of these effects are attributed to direct and multiple reflections from the scene, as well as amplitude and phase distortions of the electromagnetic waves as they penetrate the medium [3–8]. Furthermore, the effects are
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exacerbated for multilayered and composite walls [9,10]. In order to aid in mitigating these adverse wall effects and enhance the capability for imaging and classification of targets behind walls, various advanced synthetic aperture radar (SAR) and multiple-input multiple-output (MIMO) radar techniques have been developed over the years to accurately estimate the wall constituent parameters. We note that in addition to TWRI, intrawall imaging is also important in many scenarios. For example, detecting and imaging of metallic reinforcement, or locating embedded water pipes and other construction materials, may assist law enforcement personnel in operational planning of counterterrorism or other hostile situations, firefighters in civilian search and rescue operations, and utility companies in planning and delivering electricity, gas, and water services.

In order to achieve high target imaging and tracking resolution in the cross and down ranges in all of the above applications, a long aperture must be synthesized and an ultrawideband (UWB) signal must be properly transmitted. This results in a large amount of space–time or space–frequency data and a long data acquisition time, together with large storage and memory requirements, which may be expensive and complex to implement. Hence, smart reduction of the data volume using compressive sensing (CS) is important in TWRI applications, as it accelerates processing and, subsequently, allows prompt actionable intelligence. It also relaxes constraints on system aperture and bandwidth and creates different design and deployment paradigms that are more flexible than those underlying conventional SAR operations. The concept of CS indeed relinquishes the dogma of the Nyquist theorem or the need for a large number of measurements, which has ruled the entire electronics industry for a very long time. It is a relatively new concept, with possibilities for application in a wide variety of areas. The capability of CS to reconstruct a sparse signal from far fewer nonadaptive measurements provides a new perspective for meeting these objectives in TWRI and GPR. Luckily, there have been several approaches reported for application of CS to radar imaging [11–15]. In general, CS for through-the-wall imaging and tracking is a hybrid of CS and urban sensing, where it enables reliable high-resolution images of indoor targets using a very small percentage of the entire data volume [16–20].

In this chapter, we outline some of our recent works in application of CS in SAR and MIMO radar imaging and tracking of multiple targets simultaneously behind multilayer or multiple walls. We also discuss the use of CS in detection of human vital signatures in such a cluttered environment. In our proposed approach, wall effects, including wave propagation through the wall and the multiple reflections within the wall, are fully accounted for by employing the full Green’s functions of layered media in image formation and target tracking and by combining them with CS for near real-time data acquisition and postprocessing of collected data. In addition to the standard CS using $l_1$-based minimization, we also present the use of total variation minimization (TVM) in a sparse reconstruction of through-the-wall and GPR targets. TVM minimizes the gradient magnitude of the image and can result in better edge preservation and shape reconstruction than standard CS. Finally, the chapter concludes with a discussion on the design of a low complexity receiver system with reduced analog to digital converter (ADC) requirements suitable for SAR, MIMO, UWB, or stepped frequency.

3.2 CS-based radar imaging of through-the-wall and GPR targets

Over the last decade, various beamforming, diffraction tomography (DT), and other imaging techniques have been developed for TWRI [1–10,21], together with associated techniques for wall parameter estimations [22–25]. Efficient DT-based techniques have also been reported for intrawall imaging, that is, the characterization of hidden objects within the wall [26]. Even though the DT-based imaging results in near real-time image processing, it requires
the full frequency measurements at each receiving antenna element and therefore does not contribute to reductions in data acquisition time or complexity and cost of the radar system. More recently, several research groups have investigated the application of CS to TWRI for scenarios when the target space behind the wall is sparse [16–20]. Most of the reported methods of CS for TWRI were developed for monostatic SAR and are only capable of imaging a target behind a single-layer wall. In urban sensing applications, however, we often encounter situations requiring us to detect and identify targets inside a building with multilayered inner walls or walls separated by a hallway. This is challenging and beyond the capability of the delay-and-sum beamforming approach based on solving a nonlinear equation in order to find the wave propagation time as it travels through the wall [3]. Moreover, one of the main drawbacks of TWRI with monostatic SAR is the long data acquisition time to synthesize an aperture. The target in TWRI is not always stationary. During a long data collection time, the target may have moved such that the imaging result is no longer valid, as the target is not in its previous position anymore. The MIMO radar system does not need aperture synthesis; thus, its data acquisition is in real time. In the following, we outline a generalized CS-based formulation of the 2D imaging of targets behind single or multilayered building walls as well as imaging of intrawall targets for both SAR and MIMO radar by collecting measurements at random frequency points and antenna locations. In addition, we discuss the application of TVM to TWRI and GPR. TVM is based on minimizing the gradient magnitude of the image and can result in better edge preservation and shape reconstruction than the standard $l_1$ minimization-based CS.

### 3.2.1 Forward model for imaging through layered walls

Figure 3.1 shows a typical scenario of TWRI with MIMO radar. The wall region may consist of a single layer or multilayered walls. The MIMO radar system consists of $P$ transmitting antennas located at $r_{tp} = (x_{tp}, z_{tp})$ and $Q$ receiving antennas located at $r_{rq} = (x_{rq}, z_{rq})$. The operating frequency covers the range from $f_{\text{min}}$ to $f_{\text{max}}$ with a frequency step $\Delta f$, resulting in $M$ frequency bins. For monostatic SAR, the transmitter and receiver are at the same location, that is, $r_{tp} = r_{tq}$, $p = 1, 2, \ldots, Q$.

Under the point target model, which ignores the multiple scattering effects, the received signal can be written as follows [20]:

$$E_s(r_{rq}, r_{tp}, k_m) = \int G(r_{rq}, r, k_m)G(r, r_{tp}, k_m)\sigma(r)dr$$  \hspace{1cm} (3.1)

![FIGURE 3.1](image-url)  
and the through-the-wall image can be reconstructed as follows:

\[ I(r) = \int_{k_{\min}}^{k_{\max}} dk \int_{L_{t_{\min}}}^{L_{t_{\max}}} dr_{tp} \int_{L_{r_{\min}}}^{L_{r_{\max}}} dr_{rq} E_s(r_{rq}, r_{tp}, k_m) \]

\[ \cdot G^{-1}(r_{rq}, r, k_m)G^{-1}(r, r_{tp}, k_m), \]

(3.2)

where \( E_s(r_{rq}, r_{tp}, k_m) \) is the received scattered field at the \( q \)th receiver location due to the illumination of the \( p \)th transmitter; \( \sigma \) is the reflectivity of the target; \( r \) is the position vector of the target; \( r = (x,z) \); \( k_m \) is the freespace wavenumber of the \( m \)th frequency; and \( G(r;r_{tp}, k_m) \) and \( G(r_{rq}, r, k_m) \) are the layered medium Green’s functions, which characterize the wave propagation process from the transmitter to the target and from the target to the receiver in the presence of wall layers. The freespace wavenumbers of the minimum and maximum operating frequencies are denoted by \( k_{\text{min}} \) and \( k_{\text{max}} \), respectively, and \( L_{t_{\min}}, L_{t_{\max}}, L_{r_{\min}}, \) and \( L_{r_{\max}} \) are the minimum and maximum extents of the transmitter and receiver elements. Given the received signal at all antenna locations and all frequency points, the image in Equation 3.2 can then be reconstructed through discretization as follows:

\[ I(r) = \sum_{m=1}^{M} \sum_{q=1}^{Q} \sum_{p=1}^{P} E_s(r_{rq}, r_{tp}, k_m)G^{-1}(r_{rq}, r, k_m)G^{-1}(r, r_{tp}, k_m) \]

(3.3)

Computation of the above imaging formula in Equation 3.3 requires an efficient evaluation of the layered medium Green’s function, which involves a time-consuming computation of Sommerfeld-type integrals [27]. To compromise between the computation time and the exact evaluation of the Green’s function, the far-field approximation for Green’s function may be used [4,10]. This is valid in most TWRI scenarios as the target is often located in the far field of the antenna aperture. The reconstructed image in Equation 3.3 can then be written as follows [20]:

\[ I(r) = \sum_{m=1}^{M} \sum_{q=1}^{Q} \sum_{p=1}^{P} E_s(r_{rq}, r_{tp}, k_m)T_{t}^{-1}(r, r_{tp}, k_m)T_{r}^{-1}(r_{rq}, r, k_m)e^{jk_m(R_{tp}+R_{rq})}, \]

(3.4)

where \( T_t \) and \( T_r \) are the transmission coefficients from the transmitter and receiver to the target, respectively, which can be derived by applying the boundary conditions at the interface of each layer or by using an equivalent cascaded transmission-line model of the layered medium [27]. \( R_{tp} \) and \( R_{rq} \) are the distances from the \( p \)th transmitter and \( q \)th receiver to the target behind the wall, respectively.

### 3.2.2 Imaging through multilayered walls with CS

For the above \( P \)-transmitter, \( Q \)-receiver MIMO step-frequency radar with total of \( M \) transmitted frequency bins, the received signal at the \( q \)th receiver due to the illumination of the \( p \)th transmitter, after discretization of received scattered field in Equation 3.1, can be written in the matrix form as follows:

\[ y_{p,q} = \Psi_{p,q}s; \quad [y_{p,q}]_m = E_s(r_{rq}, r_{tp}, k_m), \]

(3.5)

where \( s \) is a weighted indicator vector defining the target space behind the wall, which is a \( K \times L \) pixel image, vectorized into a \( KL \times 1 \) column vector. In essence, each element of vector \( s \) represents the target reflectivity, \( \sigma \), at a given image pixel. The target space and measured data are related through the wall’s “dictionary” \( \Psi_{p,q} \), which is an \( M \times KL \) matrix,
encompassing the two-way wave propagation through the multilayered wall. Utilizing the far-field representation of the Green’s functions, the \((m,n)\)th element of \(\Psi_{p,q}\) may be expressed as follows:

\[
[\Psi_{p,q}]_{m,n} = T_\ell(r_{rq}, r_n, k_m)T_r(r_n, r_{tp}, k_m)e^{jk_m(R_{tp}+R_{rq})},
\]

(3.6)

where \(R_{tp}\) and \(R_{rq}\) are the distances from the \(p\)th transmitter and \(q\)th receiver to the target, respectively.

As opposed to the standard beamforming technique using data measured at all antenna locations for all frequencies, in order to reduce the amount of data in CS-based TWRI, we measure at a random subset of \(J\) frequencies at each receiver location, where \(J \ll M\). Then the measurement data at the \(q\)th receiving antenna can be written as follows:

\[
y_{p,q} = \Phi_{p,q}\Psi_{p,q} s,
\]

(3.7)

where \(\Phi_{p,q}\) is a measurement matrix in which each row has only one nonzero element, which is equal to one. The location of this valued-one element corresponds to the index of the measured frequency bin in the transmitting frequency sequence. In essence, the above measurement matrix is formed by randomly choosing \(J\) rows from \(\Psi_{p,q}\). In addition to the random frequency sampling, to further reduce the MIMO radar measurement data, we randomly select \(Q_r\) receivers from the total \(Q\) receivers, \(Q_r < Q\), and \(P_t\) transmitters from the total \(P\) transmitters, \(P_r < P\). These will further reduce the complexity and cost of the MIMO radar system for TWRI.

For coherent processing of the received data, we superpose the matrix equation in Equation 3.8 for all \(Q_r\) receivers and \(P_t\) transmitters to form a large matrix: \(y = \Phi \Psi s = \Omega s\). The reconstruction of \(s\) is then a sparse constraint optimization problem. From [28,29], assuming \(\Theta\) satisfies the restricted isometry property robust reconstruction of a sparse image under noise-corrupted data can be achieved by solving the convex optimization problem in Equation 3.8, which is also referred to as the Dantzig selector:

\[
\hat{s} = \arg \min ||s||_1, \text{ s.t. } ||\Theta^T(y - \Theta s)||_\infty < \delta,
\]

(3.8)

where \(\delta\) represents a small tolerance error, which can be determined using the cross-validation strategy in [15,29] for an automatic selection of the error in the optimization process. In (3.8), \(\cdot\) is the \(l_1\)-norm.

In the following, we present numerical examples for different wall-target scenarios for SAR and MIMO radar imaging through single-layer and multilayered walls. The Dantzig selector solver in the sparse constraint optimization package \(l_1\)-magic [30] is employed to solve Equation 3.8. For calculation of transmission coefficients in Equations 3.4 and 3.6, we assume that the wall parameters are known and used in the imaging. We refer the reader to [22–25] for the estimation of parameters for single-layer or multilayered walls using time and frequency domain methods.

In the first example, we investigate the imaging of a rectangular Perfect Electric Conductor (PEC) target behind a single-layer homogeneous wall in Figure 3.2a using SAR. The scattered data are simulated using the 2D finite-difference time-domain method and then Fast Fourier Transform (FFT) is performed to get the frequency domain data. The target is \(0.3 \times 0.2\) m and is \(1.5\) m away from the front boundary of the wall. The permittivity, conductivity, and thickness of the wall are \(\varepsilon_r = 6\), \(\sigma = 0.03\) S/m, and \(d = 0.2\) m, respectively. The SAR scans the region of interest at a standoff distance of \(0.3\) m, synthesizing a \(2\) m aperture with \(0.05\) m interelement spacing. The operating frequency ranges from 1–3 GHz with 61 equally spaced frequency bins. Figure 3.2b shows the imaging result using the back-projection through-wall beamformer in Equation 3.4 with full data, that is, data
FIGURE 3.2
Imaging of target behind a single-layer wall with synthetic aperture radar (SAR): (a) simulation geometry; (b) beamforming result with full data; (c) beamforming result with limited data; (d) compressive sensing (CS) imaging result with limited data; (e) CS imaging result with 20% random noise (Figure 3.2b through d). (From Zhang, W., and Hoorfar, A., IEEE Antennas Wireless Propag. Lett., 14, 1052–1055, 2015. With permission.)
measured at all frequencies and all antenna locations. The true region of the target is indicated with a white rectangle. If only two frequencies are randomly measured at each antenna location, the through-wall back-projection beamformed image appears as shown in Figure 3.2b; the image is blurred and distorted and has higher sidelobe levels. By exploiting the sparsity of the image space and solving the sparse constraint optimization problem in Equation 3.8 with the same two randomly measured frequencies at each antenna location, we obtain the reconstructed image shown in Figure 3.2c and d for noiseless and noisy data. As seen from the CS imaging result in Figure 3.2d, with only 3.3% of the full set of data, the CS method gives an even sharper and less cluttered image than the beamforming approach using the full set of data in Figure 3.2b.

The next example is the imaging of multiple targets behind external and interior walls separated by a hall wall using MIMO radar, as shown in Figure 3.3a. The dielectric constant, conductivity, and thickness of the exterior and interior walls are each $\varepsilon_b = 6, \sigma_b = 0.03 \text{ S/m}$, and $d = 20 \text{ cm}$, respectively. The width of the hall way between the exterior and interior walls is 1.2 m. The targets under investigation are rectangular and circular cylinders [20]. The MIMO radar consists of 4 transmitters equally spaced from $-1$ to 0.7 m and 18 receivers equally spaced from $-1.22$ to 1.16 m. The operating frequency covers the range from 1 to 3 GHz with 51 equally spaced frequency bins. Figure 3.3b shows the imaging result using

![Simulation geometry](image_url)

**FIGURE 3.3**
Imaging of targets behind walls separated by a hall way with MIMO radar: (a) simulation geometry; (b) beamforming result with full data; (c) CS imaging result with limited data. (From Zhang, W., and Hoorfar, A., *IEEE Antennas Wireless Propag. Lett.*, 14, 1052–1055, 2015. With permission.)
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Equation 3.4 with full data, that is, data collected at all 18 receivers and all 51 frequencies. To reduce the complexity and cost of the MIMO radar system, we randomly collected data at five receivers, and measured five random frequencies at each receiver and applied CS according to Equation 3.8. From Figure 3.3c, it is clear that the above Green’s function–based CS approach is successful for accurately geolocating and imaging the two targets behind multilayered walls using MIMO radar with a significantly reduced number of both receivers and frequencies. This will drastically reduce the complexity and cost of the MIMO radar system for TWRI.

3.2.3 Intrawall and GPR imaging using CS

The far-field Green’s function approximation for the multilayered wall model used in the above section does not lend itself to the intrawall imaging of objects inside a wall or target imaging in the GPR case. For those configurations, it is necessary to employ the Green’s function of a half-space medium in Equations 3.1 through 3.3:

\[
G(r_{rp}, r, k_m) = \frac{j k_m}{4\pi} \int_{-\infty}^{\infty} F(\alpha, k_m) \exp(j k_m \alpha (x_{rp} - x) + j k_{1z} z_{rp} - j k_{2z} z) d\alpha
\]

\[
F(\alpha, k) = \frac{2}{k_{1z} + k_{2z}}, \quad k_{1z} = k \sqrt{1 - \alpha^2}, \quad k_{2z} = k \sqrt{\varepsilon_r - \alpha^2},
\]

where \( r_{rp} = (x_{rp}, z_{rp}) \) and \( \varepsilon_r \) is the complex permittivity of the wall for interwall imaging or the ground for GPR imaging. A similar equation also holds for \( G(r, r_{tp}, k_m) \) with \( r_{tp} = (x_{tp}, z_{tp}) \). The integral in Equation 3.9 can be efficiently evaluated using the stationary phase method (SPM):

\[
G_{SPM}(r, r', k) \approx \frac{j}{4k} F(a_0, k) e^{jk\Phi(a_0)} \sqrt{\frac{2}{\pi k |\Phi''(a_0)|}} e^{j\pi/4},
\]

where

\[
\Phi(\alpha) = \alpha |x_r - x| - z \sqrt{\varepsilon_r - \alpha^2 + z_r \sqrt{1 - \alpha^2}}
\]

and \( a_0 \) is the saddle point that satisfies \( \Phi'(a_0) = 0 \). The corresponding half-space’s medium dictionary can then be written as follows:

\[
[\Psi_{m,n}]_{p,q} = G_{SPM}(r_{rp}, r, k_m)G_{SPM}(r_q, r_{tp}, k_m)
\]

We note that for a lossless wall, \( a_0, \phi, \phi', \phi'' \) are not functions of frequency and can be precomputed and stored for a given wall scenario. This would significantly speed up the CS-based imaging, especially when dealing with a large target space.

Figure 3.4 shows the application of CS to SAR imaging of a 1 \( \times \) 30 cm metallic plate hidden inside of a 20 cm dielectric wall with \( \varepsilon_r = 6 \). The receiving antenna aperture is 2 m long with an interelement spacing of 5 cm. The frequency range is 1–2.6 GHz with 55 frequency bins. Standard beamforming results using the full data set and the random number of frequency points together with the sparse reconstructed images using CS are shown in the figure. The image with the full data set of 55 frequency bins shows the target inside the wall as well as the front and back of the wall. As shown, CS-based images using only three frequency bins accurately localize the target and remove the wall clutter seen in conventional beamformed images.

We note the above CS-based imaging using the SPM evaluation of the half-space Green’s function can also be used in GPR target imaging.
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FIGURE 3.4
Intrawall imaging with SAR: (a) simulation geometry; (b) beamforming result with full data; (c) beamforming result with limited data; (d) CS imaging result with limited data.

3.2.4 Through-the-wall and GPR imaging using TVM

The standard CS techniques are mainly effective in detecting the presence of targets, but they cannot accurately reconstruct the target shape and/or differentiate closely spaced targets from an extended target. However, the TVM is based on minimizing the gradient magnitude of the image and can result in better edge preservation and shape reconstruction than standard $l_1$ minimization-based CS. It has been previously applied in image compression [31]. Unlike the standard CS, where $\|s\|_1$ is minimized, the TVM technique minimizes the total gradient of $s$:

$$\hat{s} = \arg \min \|s\|_{TV}, \text{ s.t., } \|(y - \Theta s)\|_2 < \delta,$$

(3.13)
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where \( \delta \) represents a small tolerance error, and

\[
||s||_{TV} = \sum_{i,j} ||\nabla s(i,j)||_{1}; \quad \nabla s(i,j) = \left[ \begin{array}{c} \nabla_1 s(i,j) \\
\nabla_2 s(i,j) \end{array} \right]
\] (3.14)

with \( \nabla_1 s(i,j) = s(i+1,j) - s(i,j) \), \( \nabla_2 s(i,j) = s(i,j+1) - s(i,j) \), where \( i \) and \( j \) run over the pixel indices in the cross-range and down-range image axis. In this work, we have used the Nesterov algorithm from [32], which uses a regularization scheme together with a smoothed version of the \( l_1 \) norm to efficiently solve Equation 3.13.

Figure 3.5 presents the application of TVM to the SAR imaging of through-the-wall targets. The full data are collected over 1–3 GHz using 81 frequency bins. As seen in Figure 3.5b, the TVM, using only three frequency points, results in a less cluttered image and reconstructs the target shape better than the standard \( l_1 \) minimization in Figure 3.5c.

Figure 3.6 shows the TVM application to the MIMO imaging of a GPR target using the SPM evaluation of Green’s function [33]. The full data set in the standard back-projection imaging uses 17 transmitters equally spaced from \(-0.96\) to \(0.96\) m and 16 receivers equally spaced from \(-0.9\) to \(0.9\) m at a height of \(0.2\) m above the ground. The dielectric constant

FIGURE 3.5
Imaging of targets behind wall using total variation minimization (TVM): (a) simulation geometry; (b) beamforming result with full data; (c) CS imaging result with limited data.  
(Continued)
FIGURE 3.5 (Continued)
Imaging of targets behind wall using total variation minimization (TVM): (d) TVM imaging result with limited data.

FIGURE 3.6
Ground-penetrating radar imaging of subsurface target using TVM: (a) imaging result with full data; (b) imaging result with limited data; (c) TVM imaging result with limited data.
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and conductivity of the ground are \( \varepsilon_b = 6 \), \( \sigma_b = 0.01 \, \text{S/m} \), respectively. The operating frequency covers the range from 0.8 to 2 GHz with a total number of \( M = 49 \) frequency bins. The target is relatively large, a \( 0.8 \times 0.2 \, \text{m} \) rectangular cylinder centered at \((0, -0.5 \, \text{m})\). The sparse reconstructed image using TVM utilizes six randomly selected transmitters and six randomly selected receivers together with eight randomly measured frequencies at each receiver location. As seen, the TVM-based MIMO GPR accurately locates the target at its true position and provides high-resolution and a clean image, which closely resembles that obtained using MIMO imaging of the full data set.

### 3.3 CS-based tracking of multiple moving targets behind walls

Stepped frequency wideband radars supported by CS can be effectively applied in the detection and tracking of multiple moving targets behind clutter. In such applications, the scattered fields from the targets can be of the same order or even weaker than those from the clutter. Many techniques have been developed to mitigate such effects, including Doppler processing [34], time-reversal techniques [35], and change detection [36].

In addition to target tracking, one of our motivations is the human vital sign detection in cluttered environments, as depicted in Figure 3.7. In general, the system to achieve detection and tracking behind a wall consists of two main components:

1. **An antenna system**, which includes a stepped frequency wideband transmitting antenna with a proper bandwidth and frequency resolution step related to the desired range resolution and maximum unambiguous range and an array of receiving antennas backed by the radar circuitry. The antenna system also includes a steerable beamforming network for scanning to multiple locations simultaneously and expanding the desired directions of arrival (DoAs) steering or an SAR operation using a switch for the multielement array.

2. **A CS-based detection and tracking algorithm**, which employs “change detection” as a preprocessing step for the received fields to remove the signals that do not interact with the targets. The measurement matrix incorporating the relation between the received signals from the scene and the target space for tracking is constructed based on the spatial steering vectors and Fourier transform matrix. Due to the sparsity of the target space, the signals can be measured at a small number of random frequencies for each antenna element [37]. Accordingly, the sparse target space can be recovered based on the corresponding randomly reduced measurement matrix by a proper reconstruction algorithm (e.g., orthogonal matching pursuit (OMP) [38]). However, this measurement

![FIGURE 3.7](image_url)

CS-based tracking.
matrix is highly coherent, which cannot always guarantee stable and accurate solutions. An improved reconstruction method needs to be sought to deal efficiently with the highly coherent columns. The resulting target locations can then be determined by merely selecting the highest peak values in the reconstructed target space for time instants. Because most CS reconstruction algorithms are associated with computationally intensive matrix operations (e.g., Cholesky decomposition), the parallelization of the CS algorithms may be necessary in order to apply this framework to real-time applications. As analyzed in [38], the OMP computational cost depends on the sparsity K of the recovered signal, the number measurements $M^{CS}N$, and the signal length $MP$ for N antennas, M frequencies and P DoAs. Hence, the total computational cost of the CS reconstruction of the DoA–range space for a particular time instant is $O(KM^{CS}NMP)$. Based on the computational complexity of the conventional method; that is, $O(M^2NP)$ [34], and because $M^{CS} < M$ and K is practically small due to the sparse target space, the computational complexity of the proposed approach is less than that of the conventional method.

### 3.3.1 CS-based joint 3D target tracking

The procedure for a combination of DoA, range, and Doppler processing, in the reverse order compared to [34], can be represented as below in Equations 3.15 and 3.16. The bandwidth of the stepped frequency radar, which consists of N antenna elements with an inter-element spacing of $d$, is sampled by M frequencies (center frequency $f_c$).

The frequency bins $f_m$ are uniformly distributed with a step size $\Delta f$. At each time instant, the received signals $y(n, f_m, t)$ from antenna elements for each frequency are spatially beamformed to resolve the targets along the DoA ($\theta$). It is followed by the inverse Fourier transform of the frequency $f_m$ to obtain the range $r$. Finally, the short-time Fourier transform is applied to capture the Doppler frequency $f_D$ of the targets using the time window $h(t)$.

$$s(r, \theta, t) = \frac{1}{N} \sum_{m=1}^{M} \sum_{n=1}^{N} y(n, f_m, t)e^{-j(n-1)2\pi d \frac{rl}{c} \sin \theta} e^{j2\pi f_m \frac{2}{\pi}}$$ (3.15)

$$\xi(f_D, r, \theta, t) = \int_{t'} s(r, \theta, t') h(t' - t) e^{-j2\pi f_D t'} dt'$$ (3.16)

Employing CS for the joint DoA–range space and using Equation 3.15, the received signals and the joint DoA–range space can be related approximately as follows [37]:

$$y(n, f_m, t) = \sum_{l=1}^{M} \sum_{i=1}^{P} s(r_l, \theta_i, t) e^{j(n-1)2\pi d \frac{rl}{c} \sin \theta_i} e^{-j2\pi f_m \frac{2r_i}{\pi}},$$ (3.17)

where the angle of arrival is sampled by $P$ directions within the desired DoA range [$\theta_1, \ldots, \theta_P$]. The range $r_l$ is from 0 to a maximum unambiguous range $r_m$. The column vectors $y$ and $x$ are obtained by stacking $y(n, f_m, t)$ and $s(r_l, \theta_i, t)$. From Equation 3.16, the full measurement can be rewritten in matrix form as follows:

$$y = \Phi \Psi S,$$ (3.18)

where $\Psi$ is the identity matrix, and $\Phi = [\phi_1, \phi_2, \ldots, \phi_{MP}]$ is the measurement matrix with $MN$ rows and $MP$ columns. In particular, the $((l-1)P+i)$th column is defined as follows:

$$\phi((l-1)P+i) = \varphi_r(r_l) \otimes \varphi_\theta(\theta_i),$$ (3.19)
where ⊗ represents the Kronecker product of two vectors. The effect of the wall can be incorporated in \( \Phi \) using the far-field representation of Green’s function, with the \((m - 1)N + n, (l - 1)P + i)\)th element of \( \Phi \) as follows:

\[
\Phi_{(m-1)N+n,(l-1)P+i} = T_t(r_n, r, f_m)T_r(r, r_l, f_m)e^{j(n-1)2\pi d \frac{m\sin \theta_i}{c}}e^{-j2\pi f_m \frac{2r}{c}}
\]  

(3.20)

Due to the \( K \)-sparsity of the joint DoA–range space, the CS-based approach signals are measured at a small number \( M_{CS}(< M) \) of random frequencies for each antenna element, reducing the data acquisition time by a factor of \( M/M_{CS} \). Consequently, the reduced \( \Phi_{CS} \) measurement matrix is constructed by randomly selecting \( M_{CS}N \) rows \( (O(K \log(MP))) \) of \( \Phi \) which corresponds to the selected frequencies. The new measurements can be expressed as randomized projections. The reconstruction of the DoA–range space is formulated as \( \|s\|_1, s.t., y_{CS} = \Phi_{CS} \Psi S \), which can be solved by the OMP algorithm.

### 3.3.2 Results for multiple target tracking

Here we present simulated results for two scenarios. In the first scenario, we consider a stepped frequency radar for 3D tracking of two moving targets in free space. The radar consists of a transmitter operating between 2.22 and 2.58 GHz with 5 MHz frequency steps \( (f_c = 2.4 \text{ GHz}) \). Hence, the number of frequency bins is \( M = 73 \). Given the bandwidth and frequency step, targets can be resolved with a range resolution of 0.417 m and a maximum unambiguous range of 30 m. The receiving array is positioned along the y-axis, centered at the origin. The array length is 0.75 m with 0.075 m displacement between elements, which corresponds to \( N = 11 \) elements. The range of the DoA angle is \([-45^\circ, 45^\circ]\) with a resolution of 1°. This scenario is shown in Figure 3.8a and consists of two moving spherical targets. Both move with the relative radial velocity of 6 m/s along straight paths. The first sphere approaches the radar, starting at a DoA angle of 15° and a distance of 18.125 m from the radar. The second moves away from the radar, starting at a DoA angle of −18° and a distance of 15 m from the radar. For Doppler processing, a Gaussian window of 0.14 s is used.

In order to verify the accuracy, the simulation result of the proposed method is compared with the result using the conventional method with the full data set. The simulation is

![DoA–range–Doppler scene of two targets in free space. (a) The scene geometry and (b) Results. The blue trace is for CS and the red trace is for the conventional method.](image-url)
performed for \(M_{CS} = 15\) (20\% of \(M\)). It is important to note that the number of randomly selected frequencies \(M_{CS}\) is governed by the sparseness of the joint DoA–range space. The resultant target locations are determined by selecting the highest peak values in the joint DoA–range–Doppler space for a particular time instant. It is demonstrated in Figure 3.8b that the proposed method shows good agreement with the conventional method.

In the second example, we consider 2D tracking of two moving spheres behind a wall as depicted in Figure 3.9a. The radius of each sphere is 10 cm and the number of frequency bins in this case is 81. The antenna array consists of 27 elements with inter-element spacing of 6.25 cm. The wall thickness is 38 cm and it has a relative permittivity of 6.5 and a loss tangent of 0.011. The white circles in the images of Figure 3.9b represent the exact locations of the targets. As seen, the CS-based results, which use only 10\% of the full data measurements using the conventional method, accurately track the movement of the targets.

### 3.4 CS-based detection of human vital signs behind walls

There have been many approaches to extracting the vital signs of subjects, which mainly focus on continuous wave (CW) Doppler radar [39], UWB radar [40], or stepped-frequency continuous wave (SFCW) radar [41]. UWB and SFCW radar systems are both superior to CW radar systems due to their capability of localization and multiple subject monitoring. Nevertheless, SFCW radar possesses several advantages over the UWB radar system such as high reliability, stability, and relatively easy implementation. Stepped-frequency radar, however, suffers from long data acquisition time [15], which leads to aliasing while capturing scattered signals. The application of CS for SFCW radar [42] can compress both the measurement frequencies and the slow time samples, significantly decreasing the data acquisition time and the amount of data to be processed.

We recently demonstrated the viability of CS-based SFCW radar for breathing rate detection [43,44]. A PEC elliptical cylinder based on the set of data for thoracic dimensions as presented in [45] is used to model a full respiration cycle as depicted in Figure 3.10 for an
average male with a height of 1.68 m. According to [46], during respiration the chest wall expands and shrinks periodically in both the anterior–posterior and lateral directions, so the travelled distance varies periodically around the nominal distance between the subject and the radar. Hence, in our simulation, the changes in the chest’s anterior–posterior and lateral diameters are described as sinusoidal models around their nominal diameters. Hence the distance between a subject and the radar receiver can be expressed as follows:

\[ d(t) = d_0 + m_b \sin(2\pi f_b t), \]

where \( d_0 \) is the distance between the receiver and thorax vibration center; \( m_b \) is the amplitude of the respiratory signal; \( f_b \) is the respiratory rate.

In conventional SFCW radar, we receive signals in \( m \) uniformly sampled frequencies, at \( n \) slow time indices. The inverse Fourier transform is applied to obtain range profiles for each time index; next, the range profile is used to locate the target. Finally, the forward Fourier transform is conducted along the slow time samples for the range bin corresponding to the subject location to show the respiratory rate in the frequency domain (see steps in Figure 3.11).

Two steps in this process render to CS implementation: the Fourier transform step, which relates the range profile and received baseband signals, and the inverse Fourier transform step, which relates the range to breathing rate. Considering a stepped-frequency radar centered at 3 GHz with a bandwidth of 2 GHz and a frequency step of 20 MHz (i.e., total number of frequency bins \( M = 101 \)), targets can be resolved with a range resolution of 7.5 cm and a maximum unambiguous range of 0.5 m. In order to verify the accuracy, the simulation results of the CS-based method are compared with the results of the conventional method over 160 slow time samples for a human torso with a respiratory rate of 20 breaths/min. Figure 3.12 illustrates that the CS-based method shows a good match with the conventional method.

The proposed method can indeed detect the respiratory rate using fewer randomly selected frequencies and slow time samples. We have also reported on using micro-Doppler signatures for human motion detection in cluttered media such as forests [47–51]. The above CS method can be also extended to vital sign detection of humans behind a wall by incorporating the wall’s Green’s function as was discussed in Section 3.1. To demonstrate through-wall applicability, we consider another simulation as depicted in Figure 3.13a [52]. The scene consists of a 1.79 m stationary breathing human located behind a wall, which is assumed to be homogeneous (\( \varepsilon_r = 2 + j0.1 \)), infinite, and composed of a single layer with a thickness of 2 cm. We consider a stepped-frequency radar centered at 3 GHz with a bandwidth of 2 GHz and a frequency step of 20 MHz. Hence, the total number of frequency bins is \( M = 101 \). The breathing rate is chosen to be 18 times/minute. The distance from the radar to the center of the human is 1.1 m. The radar is placed to face the wall with a standoff distance.
Imaging and Tracking of Targets behind Walls

Conventional

Received baseband signal

\[ y(f_{b}, t_n) \]

Apply CS

Range profiles

\[ x(r_{l}, t_n) \]

Determine the location

\[ x(R_{0}, t_n) \]

Respiratory rate

\[ f_{b} \]

CS based

CS step 1
(DFT)

Apply CS

\[ \mathbf{x} = \Phi_{\text{IDFT}} \mathbf{y} \]

CS step 2
(IDFT)

\[ f_{b}^b(R_{0}) = \Phi_{\text{IDFT}} N \times N x(R_{0}) \]

Slow-time

\[ t_1, t_2, t_3, \ldots \]

FIGURE 3.11
Conventional versus CS-based system for breathing.

(a)

(b)

(c)

SIMULATION RESULTS FOR BREATHING RATE IN FREE-SPACE CS VERSUS CONVENTIONAL:

(a) synthesised range profiles;

(b) reconstructed respiratory pattern;

(c) reconstructed respiratory rate.

FIGURE 3.12
of 0.4 m. The transmitter is assumed to generate a \( z \)-polarized plane wave propagating along the \( +x \) direction to illuminate the scene. The simulation is run for 20 seconds, corresponding to 400 slow time samples. The results are shown in Figure 3.13b and c.

The CS experiment is performed for \( M_{CS} = 30\% \) (which corresponds to 30\% of 101) and \( N_{CS} = 160 \) (which corresponds to 40\% of 400). In order to verify the accuracy, the
simulation results of the CS-based method are compared with the results of the conventional method. Figure 3.14b and c demonstrates that the CS-based method can detect accurately the breathing rate of a human and shows a good match with the conventional method. It indicates that the human has a breathing rate of 18 times/min, corresponding to a frequency component of 0.33 Hz.

Experimental results on human respiration behind the wall are presented after a brief description of the hardware development in the following section.

### 3.5 CS-based receiver hardware design and experiments

#### 3.5.1 CS-based stepped-frequency signal processing

Let us assume that the entire bandwidth of the system ranges from $f_0$ to $f_{N-1}$, with a center frequency $f_c$, and is sampled by $N$ frequencies, with a step size $\Delta f$. To speed up data acquisition, the SFCW radar operates using a P-channel operating in parallel—thus reducing the acquisition time by a factor of $N/P$. Meanwhile, the target range space is divided into multiple range bins $r_l$ from 0 to $r_{N-1}$, where $r_{N-1}$ is the maximum unambiguous range. The relationship between the received baseband signal $y(f_n)$ from all the channels and the range profile $s(r_l)$ can be expressed as a Fourier transform as follows:

$$y(f_n) = \sum_{l=0}^{N-1} s(r_l) e^{-j2\pi f_n \frac{2r_l}{c}}$$  (3.22)

Equation 3.22 can be rewritten in a matrix form as $y = \Theta s = \Phi \Psi s$, where $y$ and $s$ are the column vectors obtained by stacking $y(f_n)$ and $s(r_l)$, $e^{-j2\pi f_n \frac{2r_l}{c}}$ and the measurement matrix $\Phi$ is chosen as the $n \times N$ identity matrix when we use all frequencies in the conventional approach.

In the CS-based approach, however, we do not use all the frequency steps due to the sparseness of the target space. Hence, the baseband signals, $y^{CS}$, are measured at a random subset $N^{CS}(<N/P)$ of frequencies for each channel. In this case, the data acquisition time is decreased by a factor of $(N/P)/N^{CS}$. Then, we follow the same procedure to retrieve the signal as explained in the previous sections.

#### 3.5.2 Two-channel implementation

As an example, we illustrate the construction of a two-channel SFCW radar here, and the whole setup is shown in Figure 3.14. The radar has a center frequency of 3 GHz and bandwidth of 2 GHz, with a frequency step of 20 MHz, which corresponds to 101 frequency samples. In this case, the targets can be resolved with a range resolution of 7.5 cm and a maximum unambiguous range of 7.5 m based on radar parameters.

In general, a multiple channel SFCW radar system can transmit a set of frequencies simultaneously via one UWB antenna over multiple channels operating in parallel using a multiplexer, where a random subset of frequencies is transmitted and the target space is reconstructed by using a CS-based algorithm with sub-Nyquist sampling. These two strategies can reduce the data acquisition time by an order of magnitude.

#### 3.5.3 Overview of the SFCW radar system

The two direct digital synthesizer (DDS) channels are synchronized using one master 1.2 GHz reference clock and integrated on one board to cover a 2 GHz bandwidth. Each
DDS channel synthesizes an IF signal with a bandwidth of 20 MHz, followed by a 50 times phase locked loop (PLL) to acquire the RF stepped-frequency signal. The center frequency of the second DDS channel is shifted by 1 GHz, so the total bandwidth of the stepped-frequency signal is 2 GHz. In our implementation, the RF stepped-frequency signal on each channel is first divided into two halves through a Mini-Circuits ZAPD-4+ power splitter. One half from each channel is combined using a multiplexer and then fed into a Mini-Circuits ZVE-8G power amplifier and transmitted through the transmitting antenna. Meanwhile, the other two halves are split again with a quadrature coupler like the Mini-Circuits ZAPDQ-4 + 90° power splitter to serve as the in-phase and quadrature-phase local oscillator. On the receiver side, the received signal is passed through a low noise amplifier (LNA) like that of the Analog Devices HMC753 wideband LNA. The received signal is then split into its four constituent components by mixing each with its corresponding local oscillator then filtering the unwanted components to acquire the baseband signals. Each baseband signal is then digitized and converted to a 14-bit digital signal and stored in a PC for further processing using a low-speed data acquisition card like the NI USB-6009. A block diagram is shown in Figure 3.15.

In the two-channel SFCW implementation, we use one reference clock to drive the two DDS chips to avoid any synchronization problems. This 1.2 GHz reference clock is divided by 24 in the first DDS chip to work as the control clock for the complex programmable logic device (CPLD), which is used to generate the digital signal to control the two DDS chips and is considered the master clock [53]. Synchronization of the two DDS chips is extremely important and is achieved by utilizing the synchronization pins on the two chips. Such a system can be extended to multiple channel operations upon increasing the number of DDS circuits as well as the number of multiplexer channels. Figure 3.16 shows a picture of the developed two-channel multiplexer.

### 3.5.4 UWB antenna

Vivaldi antennas have been widely used in UWB applications due to their simple structure, wide bandwidth, and high gain. A Vivaldi subarray consisting of eight antipodal Vivaldi elements [54,55] was utilized in this SFCW radar implementation. It has a gain of 11.5 ± 1.5 dB from 2 to 4 GHz and also has a constant radiation pattern over the entire frequency range.

The full Vivaldi array (shown in Figure 3.17) is comprised of eight subarrays and has an 0.8 wavelength at the highest operating frequency (4 GHz) to prevent grating lobes.
FIGURE 3.16

FIGURE 3.17
Eight-element Vivaldi ultra-wideband antenna.

within the limited scanning range. More details about the antenna design can be found in [55].

Based on adequate measured decoupling between the different subarrays, we can assume that all array elements are the same and independent of their location along the linear array; otherwise the calculation of the received signals will be impractical. To automate the full array; one single-pole eight-throw (SP8T) switch was designed and is shown in Figure 3.16.
In the SAR operation, one wideband Vivaldi element is used for transmitting, while an eight-element Vivaldi antenna array (shown in Figure 3.17) is utilized for receiving. The SP8T switch is sequentially connected to one of the eight subarrays to acquire a real aperture SAR image in the horizontal plane. For full imaging capability, both transmitting and receiving antennas can be mechanically steered in the elevation direction. Both simulation results and actual measurements indicate that the CS-based signal processing method allows for a reduction in the number of transmitted frequency points while still attaining performance comparable to that of the traditional inverse discrete Fourier transform (IDFT) method, which needs to process the full data set.

In MIMO operation, multiple transmitters and receivers are used to transfer more data at the same time. MIMO utilizes spatial diversity, as receiving multiple spatial streams simultaneously (if coherently combined) would significantly enhance performance. Upon combining these data streams arriving from different directions (angles) and at different times, the signal power is coherently added, thus increasing the signal power. By increasing the number of receiving and transmitting antennas, the signal power could increase linearly with every pair of antennas added to the system.

In our implementation here, we used single-input multiple-output, where the transmitter has a single antenna and the receiver has multiple independent antennas. The same setup used above for SAR can be utilized as well for MIMO operation, where one antenna is used as a transmitter and more than one antenna can be used as independent receivers.

### 3.5.5 Experimental results

An experiment was carried out [56] to identify the respiration of two stationary persons, standing at different distances to the radar sensor behind the wall, as shown in Figure 3.18a. The radar sensor has accurately separated two targets by the down range (i.e., distance to radar sensor), as shown in Figure 3.18b, which shows that the first person is at a down range of 3.2 m and a cross range of 2.1 m, whereas the second person is at a down range of 2 m and a cross range of 2.9 m. The range profile is demonstrated in Figure 3.18c, which introduces a respiratory rate of 18 breaths/min from the first person and 21 breaths/min from the second person, because radar return signals from the two persons are at distinct range bins. Both conventional and CS were applied on the slow-time sampled pulse at related range bins to acquire the Doppler frequency spectrum, as shown in Figure 3.18d and e, which show a Doppler frequency of 0.29 Hz from the first person and 0.34 Hz from the second person.

To validate the proposed CS technique, one non-line-of-sight experiment was conducted in an indoor environment using an SFCW radar system. The two-channel SFCW radar system had a total bandwidth of 2 GHz. The frequency step and duration for each frequency step were 20 MHz and 50 μs, respectively. As a result, a maximum unambiguous distance of 7.5 m was achieved. To be consistent with the simulation setup, the frequency steps were programmed to be 101 and a total of 400 frames were collected during the experiments.

In this experiment, one sedentary subject with a height of 1.79 m was breathing normally and standing 1.1 m away from the radar system. A wooden wall was located 0.4 m away from the radar. When $M^{CS} = 30$ (30% of 101) was performed on frequency samples, it was shown (Figure 3.19a) that the respiration signal detected with the CS-based method matched well with the one recovered using the conventional method. The experiment was performed for $M^{CS} = 40$ and $N^{CS} = 160$ (40% of 400) as well, and a respiration rate of 0.33 Hz was accurately detected using the CS-based method, as shown in Figure 3.19b.
FIGURE 3.18
Localization and respiration detection of two persons through a cement wall: (a) experimental setup; (b) localization of the two human targets; (c) range profile versus time; (d) Doppler frequency spectrum due to the breathing of the first person; (e) Doppler frequency spectrum due to the breathing of the second person.
3.6 Conclusion

In this chapter, we presented highlights of some of our work on imaging and tracking of targets behind or inside building walls using CS and discussed a CS-based method for detection of human vital signs. For through-the-wall imaging and tracking, our approach used the far-field approximation of multilayered Green’s functions to fully account for all the wall effects, whereas for the intrawall and GPR imaging, we used a saddle-point approximation of the half-space Green’s function. In addition to standard CS, we also presented the use of TVM in sparse reconstruction of through-the-wall and GPR targets. Finally, in this chapter, we outlined the hardware design of a multiple channel step-frequency radar system that included a low-complexity receiver system for efficient implementation of the proposed CS-based target imaging, tracking, and human vital sign detection. Simulated and experimental results were presented to demonstrate the effectiveness of the proposed CS-based techniques.

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References


