Study of Compressive Sensing on through Wall Imaging

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ABSTRACT
The theory of Compressive Sensing (CS) enables the reconstruction of sparse signals as well as image from small set of random measurements by solving primal dual interior point method for l1 minimization problem.

This paper presents reconstruction of signal based on CS theory applied on experimental data. Reconstruction of A-scan and B-scan image with fewer samples is obtained without affecting quality. Reconstruction of range profile with A-scan data with random samples by inverse discrete frequency transform (IDFT) is achieved and then compares it with CS reconstructed range profile by computing peak signal to noise ratio (PSNR). It is observed that PSNR obtained with CS has good quality while using IDFT, it is degraded. Similar results are obtained for B-scan image.

General Terms
Signal processing, compression.

Keywords
CS,l1, PSNR Stepped frequency continuous wave (SFCW), through wall imaging (TWI).

1. INTRODUCTION
Imaging of objects in through wall and other visually opaque materials, using microwave signals have become a major area of interest in a variety of applications like military on one side and commercial paradigms on other. For example, TWI can be used in rescue missions, surveillance and reconnaissance, bomb disposal, hostage rescue etc.

Research in through wall detection and imaging evolved about electromagnetic and radar signal processing. One of the major thrusts will be developing more efficient imaging algorithms [1-2]. The challenging aspect for through wall imaging system is to produce high quality images with speed. High down range and cross range resolutions are required for high quality images. For these purpose, TWI radar system requires UWB pulse to achieve high down range resolution and large antenna aperture to achieve cross range resolution [3].

UWB pulse can be generated using SFCW radar system and Synthetic aperture technique is used to provide better cross range resolution to avoid large physical array antenna [4]. In SFCW, the frequency of successive pulses increases linearly in discrete steps. SFCW radar attains a large effective bandwidth and thus provides high resolution with the advantages of narrow band system [5]. The problem with this system is huge data collection and long acquisition time. CS can be used to reduce data and acquisition time without affecting quality of images.

According to Nyquist sampling theorem, sampling frequency must be at least two times greater than maximum frequency of the signal in order to avoid losing information while capturing a signal. In multimedia applications, Nyquist theorem results in too many samples hence compression is necessary. Sometimes this increase in sampling rate becomes expensive as in medical applications. Nyquist theorem is still valid; one byte in a signal or image of white noise is skipped, does not restore the original. But most interesting signals and images are not white noise, rather have relatively few non-zero coefficients when represented in proper basis functions & termed as sparse in compressive sensing [6].

In data acquisition systems, transform coding plays a vital role: the full N-sample signal $\boldsymbol{x}$ is acquired & the complete set of transform coefficients $\{s_i\}$ is computed; the K largest coefficients are located & encoded but $(N - K)$ smallest coefficients are discarded. Unfortunately, this sample & then compress frame work suffers from three inherent inefficiencies. First, the initial number of samples N may be large even if the desired K is small. Second, the set of all N transform coefficients $\{s_i\}$ must be computed even though all but N-K of them will be discarded. Third, the locations of the large coefficients must be encoded, thus introducing an overhead [7].

This paper focused on the problem of SFCW based radar system. Extremely sparser images can be obtained when CS is applied to SFCW data compared to standard back projection imaging algorithms [8].Using CS ground reflections are removed for shallow targets [9].Conventional matched filtering increases SNR with increase in sidelobes. But radar imaging based on CS method is alternative to it [10].Using CS technique 1/3 of sampling rate is reduced as compared to traditional correlators [11].

Yoon and Amin [12] propose a method in which CS is applied to reduce samples along frequency axis at each antenna location and then imaging algorithm delay sum beamforming is applied. Huang et al [13] proposes algorithm based on CS that accurately reconstructs the target space image with lower sidelobe level than conventional delay sum beamforming method. To improve the performance of CS based through wall imaging, priory information such as target RCS is used by Amin, Ahmed and Zhang [14]. Duman and Gurbaz [15] discusses effects of error in wall parameters on CS based imaging. All CS application on TWI data is carried out by various researchers; it lacks analysis of effect of CS on imaging. This work compares A-scan and B-scan data obtained with and without application of CS principle. The paper is organized as follows. In section 2, description of CS theory is given. Section 3 describes about experimental setup and system. Results obtained by application of CS on through wall imaging experimental data are given in section 4. Finally conclusions are given in section 5.

2. CS THEORY

2.1 Principle of CS

Theory of CS is well reported in literature. It is briefly discussed here for the sake of continuity.

Consider a discrete-time signal $\vec{s}$ of length N. After transform coding, the signal changes into Ψ, the signal changes into

$$\vec{S}=\Psi\cdot\vec{s}. \quad (1)$$

The transform Ψ **is** represented as an $N\times N$ orthogonal/ unitary matrix which have strong decorrelation property for making most of the coefficients as small as possible & ignoring few of them. For converting a spatial or temporal signal into few dominant coefficients, wide range of unitary transforms, such as fast Fourier transform, discrete cosine transform, discrete wavelet transform, etc., are available. In fact, this is the working principle behind modern compression techniques. When the magnitudes of the transform-domain coefficients are plotted against transform coordinates, they decay quickly. Such a signal will be called a sparse signal, and the transform Ψ that enables this property will be attributed as the sparsity transform.

In CS, reconstruction of the sparse signal $\vec{s}$ requires just a small number of entries in $\vec{s}$. This subsampling process can be represented as projection by an $M \times N$ measurement matrix Φ, where $N>>M$. Therefore, the observable $\hat{\vec{s}}$ can be expressed as

$$\hat{\vec{s}} = \Phi\Psi^{-1}\vec{S} = \Delta\cdot\vec{s}. \quad (2)$$

The newly defined matrix $\Delta \equiv \Phi\Psi^{-1}$ represents an overcomplete basis. Equation (2) expresses an underdetermined system of linear equations, where the number of unknowns, which are the components of vector $\vec{s}$, is larger than the number of linear equations whose coefficients are included in Δ, so that the solution will be nonunique. To solve this equation, CS assumes that the signal is sparse, which means that the number of transform-domain coefficients, i.e.,

$$\|\vec{S}\|_0=\sum_{n=1}^{N}|S_n|^0 \quad (3)$$

is minimum. However, minimization of (3) is a combinatorial problem that is computationally intractable. When the signal is highly sparse, the solution of (3) for $L0$ is identical to the solution of a more tractable $L1$ problem by minimizing

$$\|\vec{S}\|_1=\sum_{n=1}^{N}|S_n|^1 \quad (4)$$

In fact, the minimization of (4) can be recast as a convex programming problem [11], whose solvers, such as the interior point method, are widely available. An important issue regarding this solution is that Φ and Ψ should be sufficiently incoherent. The measure of coherence between two bases $\mu(\Phi, \Psi)$ is defined by

$$\mu(\Phi,\Psi) = \max_{\Phi\in P,\Psi\in S}|<\Phi,\Psi>| \quad (5)$$

where P and S are sets of column/row vectors of the matrices Φ and Ψ, respectively. Recent findings in CS show that a general random basis has a high degree of incoherence with any basis, including the identity or spike basis. Therefore, we can choose a random matrix as the projection basis Φ. In such a basis, the number of required samples K must satisfy

$$K \geq C \cdot \mu^2(\Phi, \Psi) \cdot F \cdot \log(N) \quad (6)$$

where C is a constant and F denotes the degree of freedom of the signal or the number of nonzero coefficients of the signal when represented in the sparsity basis Ψ. For the A-scan data, where the impulse is modeled as a monocycle, the degree of freedom is proportional to the number of objects or reflectors that interact with the wave along its propagation. Equation (6) shows that the required number of samples in CS is reduced logarithmically. Although, in its original form, the constant C is not specified explicitly, researchers found empirically that $C < 1$, and when $N \sim 1000$, an F sparse signal, i.e., a signal with F degree of freedom, can be reconstructed exactly from its $2F$ random samples [7].

For a suitable number of measured data K given by (6), CS guarantees to recover perfectly the time-domain signal through optimization

$$\min_{\vec{S}}\|\vec{S}\|_1 \quad \text{s.t.} \quad \hat{\vec{s}} = \Phi\Psi^{-1}\vec{S} \quad (7)$$

where Ψ^{-1} is the inverse of Ψ.

In brief, the CS principle states that, for a small but sufficient number of observations, it is possible to recover exactly an original sparse signal $\vec{s}$ from its subsamples $\hat{\vec{s}}$ through $L1$ Optimization given by (7). Detailed explanations on the optimization given by (7) can be found in [16].

CS theory asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use. To make this possible, CS relies on sparsity, which pertains to the signals of interest.

3. MEASUREMENT SETUP AND DATA ACQUISITION

The experimental setup is shown in Figure 1 to perform B-scan measurements. A plywood wall is used and metal plate as a target. The relative permittivity of wall is 5.5 within the frequency band 3.95 GHz to 5.85 GHz SFCW radar is assembled using R&S ZVL vector network analyzer (VNA),C band pyramidal rectangular horn antennas and circulator. In this experiment, a square shape aluminium sheet with 0.2 cm in thickness and 58 cm in dimension was kept behind wall at a distance of 30 cm away from wall. Transmission coefficient (S_{21}) measurements were collected along a straight path of 130 cm with 26 discrete spatial points at proper height so that target reflections are observed. For each spatial point, the VNA's frequency is varied from 3.95 GHz to 5.85 GHz with 4001 discrete frequency points and transmits power as 20 dBm. The distances of scanning system with wall dimensions of target is shown in Table 1. Presentation of data obtained by experimental setup can be in the form of scans: A and B scans. In all the cases the target plate was placed on a stand at a height of 0.55 m above the scanner first position and the scanner first position is 0.46 m above ground.

Table1. Data collection for experiment

Sr. No	Shape of target	Size of target	Distance between wall and antenna	Distance between wall and target
1	Square	0.58 m^2	2.32 m	0.3 m

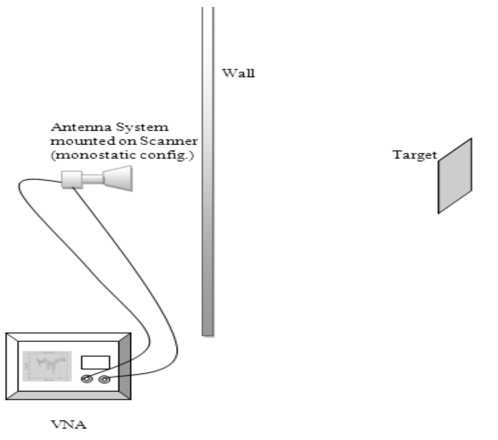


Fig 1: Experimental set up

4. RESULT AND DISCUSSION

Before applying imaging algorithm preprocessing technique i.e. calibration and velocity correction is applied as described [17]. Since the velocity of waves decreases when they pass through wall, velocity correction is required so that target will not appear displaced from its original position. The dielectric constant and thickness of wall is assumed to be known to apply velocity correction.

Single dimensional signal or range profile is generated using complete TWI radar data called as a reference called as original signal which is plotted as shown in Figure 2 (a). For sake of simplicity, 63 samples are taken i.e upto the 5 m in down range. Peaks due to different scatterer can be observed in the Fig. 2(a). It is found that the first peak is due to weak isolation between transmitting and receiving port of the system. Second and third peak represent reflection from wall and target respectively. The aim behind plotting the range profile was to know the number of peaks and peak representing target. By keeping antenna position fixed & varying frequency in step interval, one signal has been generated with obviously 63 samples. After this l1-reconstruction algorithm is used with random number of samples (i.e. less than 63) & recovered signal now becomes CS signal which resemble with previously generated signal.

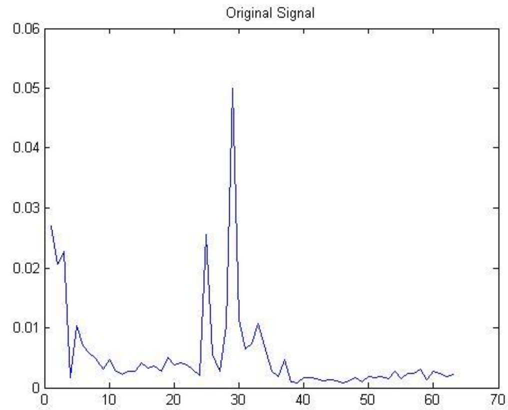
4.1 Experimental analysis with A-scan data

To analyze CS imaging, select a subset of Fourier coefficients randomly. First out of total 63 original sample points, reduced random samples are selected. Direct inversion of these random samples by IDFT gives distorted curve with lower value of peak to signal noise ratio. On the other hand, l1 optimization in CS method provides good reconstruction with higher PSNR. In CS method increased in random samples increases PSNR value. Here PSNR values are calculated for random samples from 35 to 55 as shown in Table 2.It is observed from Figure 2(b) and Figure 3 that quality of reconstruction is determined by number of samples. If the numbers of samples are more, quality of signal is good.

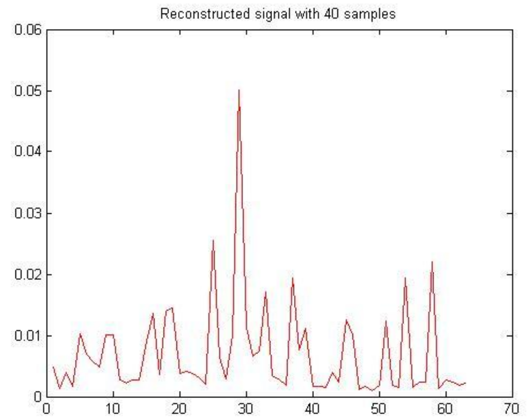
But when reconstructed the signal with direct inversion by IDFT it generates distorted curve as shown in Figure 4.

Table 2: Performance comparison of direct IDFT & CS reconstruction

Sr. No.	No. of samples	PSNR-IDFT(dB)	PSNR-CS(dB)
1	35	12.33	14.01
2	40	12.37	14.80
3	45	12.43	15.78
4	50	12.44	17.76
5	55	12.51	17.98

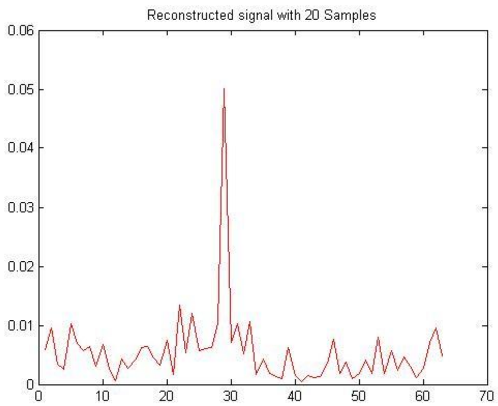


(a)

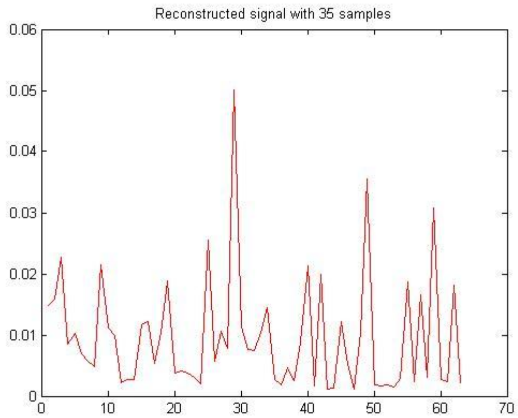


(b)

Fig 2: (a) Original, (b) Reconstructed signal with 40 samples



(a)



(b)

Fig 3: Reconstructed signal with samples (a) 20 (b) 35

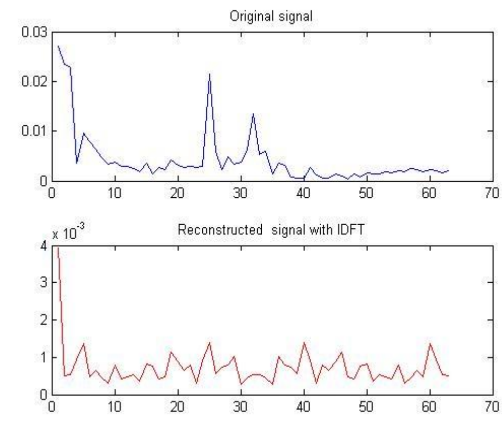


Fig 4: (a) Original (b) Reconstructed signal with IDFT

4.2 Experimental analysis with B-scan image

For target detection process, 2D information can be important. From Table 2, it is observed that maximum value of PSNR is obtained for 55 random samples. B-scan image has been reconstructed by collecting all 26 A-scans via compressive sensing technique with 55 samples & compared it with original B-scan image. Original B-scan image is shown in Figure 5. Partial random sampling is performed with 1.14 compression factor. The direct IDFT image reconstruction is shown in Figure 6 which shows significant degradation. On the other hand, CS reconstruction for same compression factor is shown in Figure 7, removes most of the defects, providing much better image than Figure 6. It is also observed that target position as well as wall position can be clearly identified

5. CONCLUSION

Encouraging results have been obtained from metallic target behind plywood wall. Random measurement reduces the number of samples thereby reduces scanning time requires to capture the image.

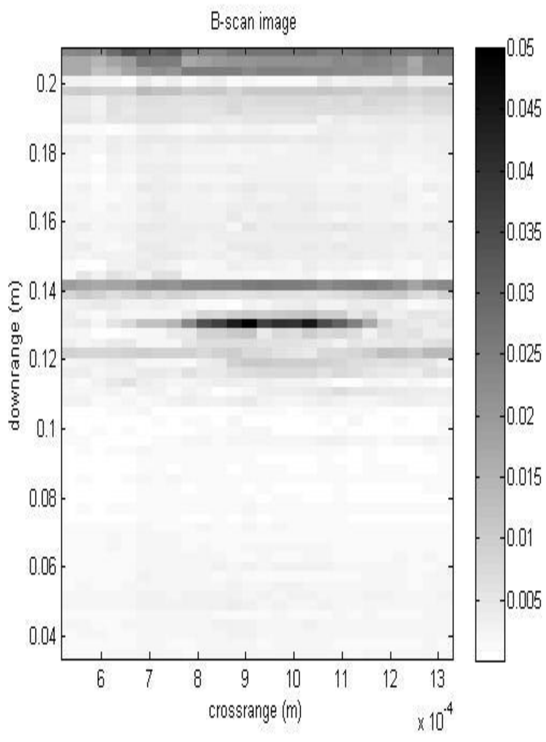


Fig 5: Original B scan image

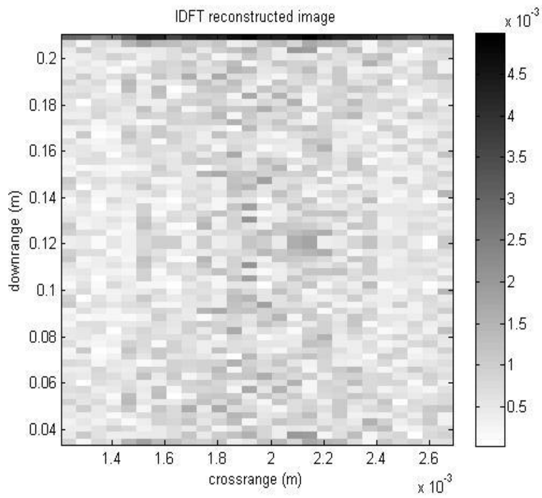


Fig 6: IDFT reconstructed image

Hence data acquisition speed has been increases significantly which was problem with SFCW based radar. In proposed

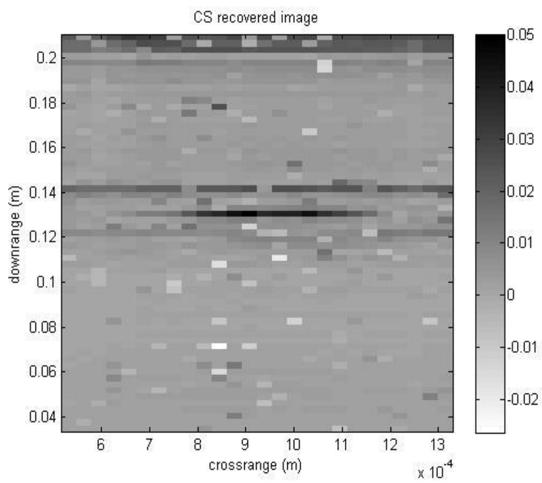


Fig 7: CS reconstructed image

method focus was on reconstruction of wall as well as target position with less number of samples which is principle point in Compressive Sensing. In future, CS technique shall be applied to reduce both antenna position as well as number of stepped frequencies.Further the performanance of the technique should be tested with more realistic scenarios such as inhomogeneous wall and its effect on CS by removing it.

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