FAST ENCODING OF SYNTHETIC APERTURE RADAR RAW DATA USING COMPRESSED SENSING

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ABSTRACT

Synthetic Aperture Radar (SAR) is active and coherent microwave high resolution imaging system, which has the capability to image in all weather and day-night conditions. SAR transmits *chirp* signals and the received echoes are sampled into In-phase (I) and Quadrature (Q) components, generally referred to as raw SAR data. The various modes of SAR coupled with the high resolution and wide swath requirements result in a huge amount of data, which will easily exceed the on-board storage and downlink bandwidth of a satellite. This paper addresses the compression of the raw SAR data by sampling the signal below *Nyquist* rate using ideas from *Compressed Sensing* (CS). Due to the low computational resources available onboard satellite, the idea is to use a simple encoder, with a 2D FFT and a random sampler. Decoding is then based on convex optimization or uses greedy algorithms such as Orthogonal Matching Pursuit (OMP).

Index Terms— SAR, Compressed Sensing, Encoding

1. INTRODUCTION

Synthetic Aperture Radar (SAR) is active and coherent microwave radar, which produces high spatial resolution images from a moving platform – an airplane or a satellite. The radar produces 2D (range and azimuth) terrain reflectivity images by emitting a sequence of closely spaced radio frequency pulses and by sampling the echoes scattered from the ground targets. The received echoes are sampled into In-phase (I) and Quadrature (Q) components referred to as raw SAR data. In satellite systems, raw data is directly transmitted to the ground segment via a dedicated transmission link when in view with the ground segment or is stored onboard for later transmission to the ground.

The compression of raw SAR data poses several challenges due to its noise like characteristics [1]. The noise like characteristics arises because signals from several scatters are added incoherently with unknown phase and amplitude. Typically its adjacent samples are uncorrelated in both range and azimuth directions.

The SAR processed images have compression factor of 50:1, which is much higher than the existing raw data compression factor of 4:1 [2]. Most of the traditional compression systems exploit the redundancy inherent in the *Nyquist* rate sampled signal to achieve compact representation and efficient transmission of the information. This technique of sampling at a higher rate and then eliminating redundancy by processing a large amount of data has poor efficiency in terms of both sampling rate and computational complexity.

A new framework that recovers signals from incomplete measurements is *Compressed Sensing* (CS), introduced in [3] and [4]. It was shown that a signal having a sparse representation can be captured (encoded) from a small number of random linear projections onto a measurement basis. The measurement process is *non-adaptive*. The original signal can be reconstructed (decoded) through a non-linear decoding scheme that uses the sparsity as *a priori* information for solving the linear inverse problem.

2. SAR SYSTEM AND PROCESSING

In the *Stripmap* mode the radar maps the surface with the antenna pointing downward such that the boresight (centre) of the mainlobe of the real aperture radiation pattern is perpendicular of the flight path as shown in Figure 1 [1]. The simplified model for the SAR *Stripmap* model is to consider the stationary imaging surface to consist of several point reflectors with reflectivity σ_n and located at the location (x_n, y_n). The radar located at (o, u_n) in the spatial domain transmits wide bandwidth signal $p(t)$ of period T_p at regular interval T_{PRI}.

The processing of SAR raw data is shown in Figure 2, which involves computation of 2D FFT, matched filtering with the scene centre reference function, converting the polar format data to the rectangular format through *Stolt mapping* and finally 2D IFFT [5].

3. COMPRESSED SENSING THEORY

Let us consider signal $\mathrm{f} \in \mathbb{R}^N$, which has a sparse representations over a fixed orthogonal transform, $\mathbf{\Psi} \in \mathbb{R}^{N \times N}$, having columns ψ_i, $i = 1,....,N$. Thus, we can describe the signal as $\mathrm{f} = \mathbf{\Psi}\,\mathrm{x}$ with $\|\mathrm{x}\|_0 \le L \ll N$, where $\|\mathrm{x}\|_0 = |(i : x_i \ne 0)|$. Such a signal is known as an $L-Sparse$ signal w.r.t. the dictionary $\mathbf{\Psi}$.

In the CS framework, to measure (encode) f we compute the measurement vector $\mathrm{y} \in \mathbb{R}^K$ using a linear projector $\mathbf{M} \in \mathbb{R}^{K \times N}, with\ L < K \ll N$ via $\mathrm{y} = \mathbf{M}\,\mathrm{f}$. Since $K \ll N$, we have fewer measurements than degrees of freedom for the signal f. We refer to $\mathbf{M}$ as the measurement matrix whose rows are the measurement vectors and denote its columns by $\varphi_1, ..., \varphi_N$.

The measurement signal $\mathrm{y} \in \mathbb{R}^K$ is written is terms of $\mathrm{x} \in \mathbb{R}^N$ as

$$\begin{aligned} \mathrm{y} &= \mathbf{M}\,\mathrm{f} = \mathbf{M}\mathbf{\Psi}^*\,\mathrm{x} \\ &= \mathbf{H}\,\mathrm{x} \end{aligned} \tag{1.1}$$

where $\mathbf{H} = \mathbf{M}\mathbf{\Psi}^*$ is also known as the holographic basis.

The original signal f can be reconstructed from y by exploiting the sparsity of its representation i.e. by searching for all possible $\hat{\mathrm{x}}$ satisfying $\mathrm{y} = \mathbf{H}\,\hat{\mathrm{x}}$ that is the sparsest. If this representation coincides with x we get a perfect reconstruction of the signal via (1.1). Mathematically, $\hat{\mathrm{x}}$ can be found by solving the linear inverse problem through l_0 optimization $\hat{\mathrm{x}} = \arg\min \|\mathrm{x}\|_0$ subject to $\mathrm{y} = \mathbf{H}\,\hat{\mathrm{x}}$. The objective function enforces the sparsity whereas the constraint enforces data consistency. The l_0 optimisation is a combinatorial problem and is NP-hard to solve. The two most common approaches are therefore to replace the l_0 approximation problem with convex optimisation methods or greedy methods [6, 7].

4. RAW SAR DATA COMPRESSION THROUGH CS

To study the feasibility of using CS for SAR raw data compression, we used five point targets simulated through the SAR simulator as shown in Figure 3(a) with ideal point target response in Figure 3(b). The 2D FFT of the complex raw data was performed, as shown in Figure 3(c), after which the data was sampled randomly. The size of the measurement data is 4200 for the image size of 256 x 256, to recover 200 samples of the sparse image representation of five targets. The reconstruction algorithm is based on OMP with the least square estimation performed through the Conjugate Gradient (CG) method. The reconstruction process involves computation of (forward and inverse) matched filtering, *Stolt* mapping and 2D FFT. The reconstructed image for the point target simulation is shown in Figure 3(d) and was evaluated in terms of the Peak Side Lobe Ratio (PSLR) and Integrated Side Lobe Ratio (ISLR). The PSLR is defined as the ratio of the peak intensity of the most prominent sidelobe to the peak intensity of the mainlobe. The ISLR is the ratio of the power in the mainlobe to the total power in all the sidelobes. The PSLR and the ISLR of the point targets simulation for 256 x 256 size complex SAR processed image and the image generated with 4200 measurement samples and 200 wavelet coefficients are tabulated in Table 1.

	PSLR (dB)	ISLR (dB)
Original Image	-11.21	-1.75
CS Image	-10.97	-4.96

Table 1. PSLR and ISLR of the original and reconstructed CS image.

There is no degradation in PSLR and the improvement in the ISLR is due to the recovery of only 200 wavelet coefficients which resulted in the reduction of the sidelobes power.

For the compression of the satellite SAR raw data, the amplitude and phase are both indispensable for many applications e.g. interferometer. Discrete Wavelet Transforms have been used for SAR intensity image compression but are not suitable to preserve the signal phase information. The compression of the complex SAR image is reported in [8] and the study of the Complex Wavelet Transform (CWT) for the SAR image compression and denoising to preserve both amplitude and phase has been reported in [9]. We propose to use the Dual Tree CWT (DT-CWT) [10], as a sparsifying transform with OMP to find the sparse representation of the complex SAR image. The DT-CWT comprises of two parallel wavelet filter banks that contain filters of different delays that minimises the aliasing error due to decimation [10]. DT-CWT has been generally applied to the real signals where the spectral decomposition takes place only for the positive part of the spectrum. For the quadrature SAR image, the spectral decompositions for both negative and positive part of the spectrum are required. This is achieved by applying the DT-CWT to the real, ξ_r, and imaginary part, ξ_i, of the complex SAR image separately and then combining the complex output as

$$\begin{aligned}\xi_+ &= \xi_r + i\xi_i \ , \\ \xi_- &= \xi_r - i\xi_i\end{aligned} \qquad (1.2)$$

where ξ_+ corresponds to the positive frequency component and ξ_- corresponds to the negative frequency component. Thus, we represent the image using a frame operator rather than a basis.

The Compressed Sensing framework for the complex SAR raw data is shown in Figure 2. The holographic basis, $\mathbf{H}$, in (1.1) is implemented through functions consisting of 2D-DT-CWT, 2D FFT, *Stolt* interpolation, matched filtering and the measurement matrix, $\mathbf{M}$, consists of random sampling points. The reconstruction is similar to the one used for the point target processing.

The OMP based reconstruction for the 2:1 compression for the actual complex SAR image was carried out for 32 x 32 size image to evaluate the PSNR with respect to various lengths of recovered wavelet coefficients and is tabulated in Table 2. The PSNR of 2:1 compressed signal degrades faster for recovery of wavelet coefficients greater than 150. This is consistent with the theory of compressed sensing to have measurement length 3 to 5 times the length of the sparse coefficients.

	50	100	150	200	250	300
Original	36.8	38.8	40.3	41.5	42.7	43.9
CS Image	36.8	38.7	39.5	39.7	39.8	39.8

Table 2. PSNR (dB) of 2:1 compressed signal with respect to the recovered wavelet coefficients.

For the 256 x 256 SAR complex image, as shown in figure 4(a), the reconstruction of the image for 6000 wavelet coefficients with OMP is shown in figure 4(b). The figure 4(c) shows the reconstruction with OMP for 6000 wavelet coefficients with 2:1 compression ratio. The reconstruction with the 6000 most significant wavelet coefficients (sorted) with DT-CWT as a frame operator is shown in figure 4(d). The reconstruction with OMP is limited to 6000 coefficients as the sparsity of the complex wavelet is not sufficient to provide any substantial improvement in PSNR of the reconstructed image. The reconstructed images with and without compression do not show much perceptual difference.

The optimization based reconstruction of SAR image with small set of measurement data has an advantage that important features required for detection, classification and registration of SAR images can be recovered without reconstruction of the full image. The recovery based on CS is thus scalable depending upon various applications.

5. CONCLUSIONS

This paper proposes the use of the CS framework for fast compression of SAR raw data to ease the computational requirements of satellite onboard processing. Much greater performance in terms of higher compression ratio and reconstruction qualities are expected by using transforms that could give better sparsity for the SAR complex signal as compared to the DT-CWT used here.

6. REFERENCES

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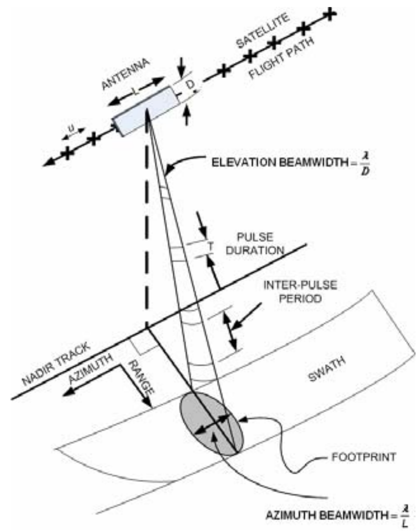

Figure 1. Geometry of Stripmap SAR.

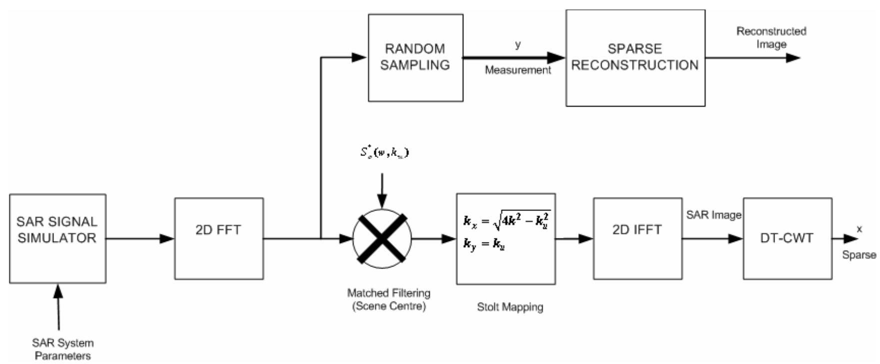

Figure 2. The Omega-K Processing of SAR data.

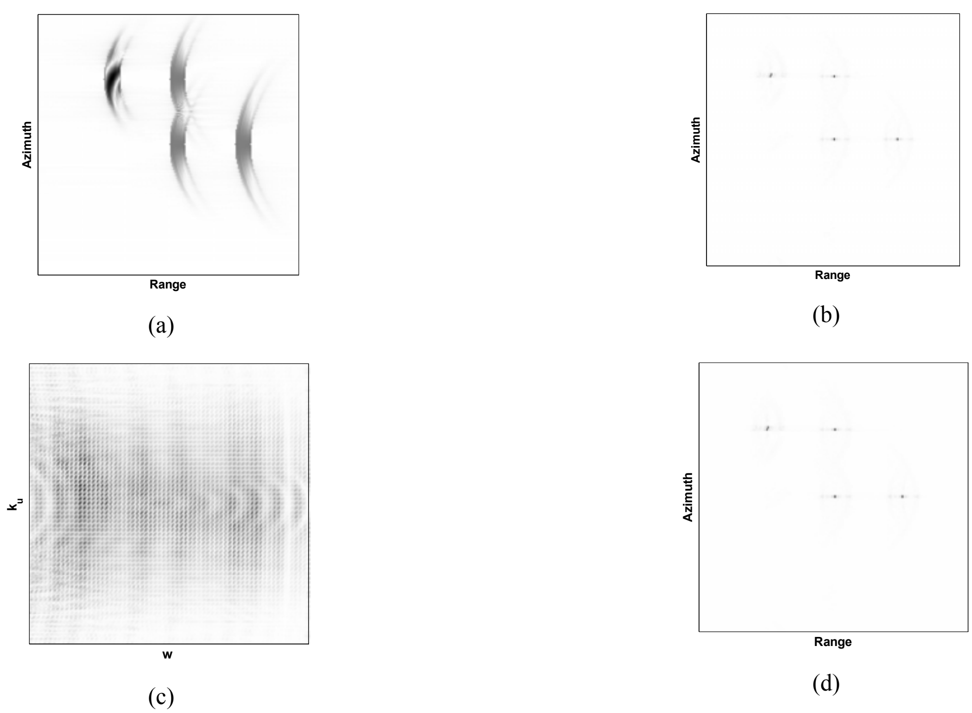

Figure 3 (a) Simulated Signal, (b) Point targets, (c) k-space Signal (d) Reconstructed Image (200 pts)

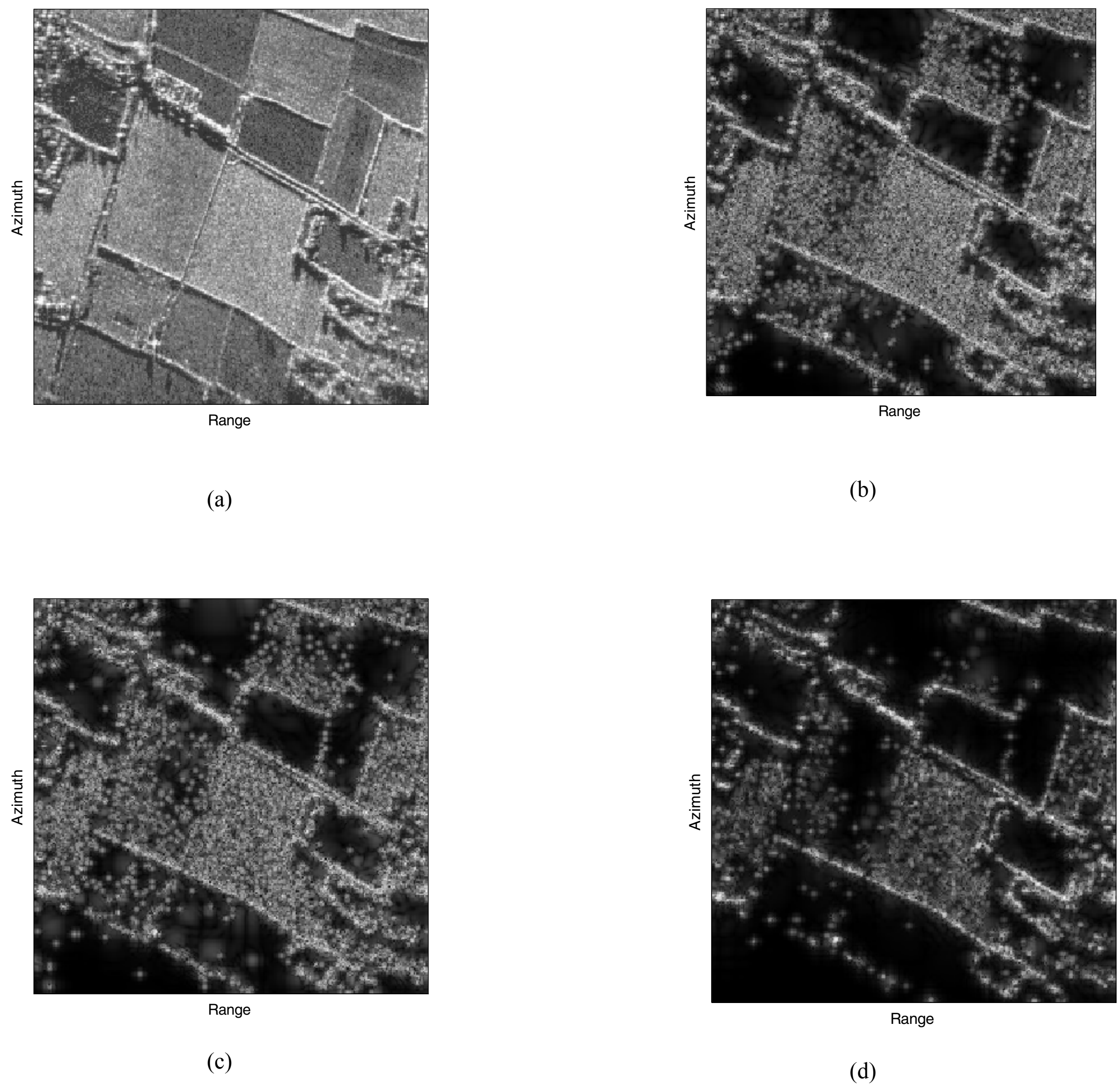

Figure 4. (a) Original SAR Image, (b) Intensity image with OMP reconstruction for 6000 coefficients, (c) Intensity image for 2:1 compression with OMP reconstruction for 6000 coefficients (d) Reconstructed Image with 6000 sorted coefficients (DT-CWT used as a frame operator).