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SAR image reconstruction by expectation maximization based matching pursuit

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ABSTRACT

Synthetic Aperture Radar (SAR) provides high resolution images of terrain and target reflectivity. SAR systems are indispensable in many remote sensing applications. Phase errors due to uncompensated platform motion degrade resolution in reconstructed images. A multitude of autofocusing techniques has been proposed to estimate and correct phase errors in SAR images. Some autofocus techniques work as a post-processor on reconstructed images and some are integrated into the image reconstruction algorithms. Compressed Sensing (CS), as a relatively new theory, can be applied to sparse SAR image reconstruction especially in detection of strong targets. Autofocus can also be integrated into CS based SAR image reconstruction techniques. However, due to their high computational complexity, CS based techniques are not commonly used in practice. To improve efficiency of image reconstruction we propose a novel CS based SAR imaging technique which utilizes recently proposed Expectation Maximization based Matching Pursuit (EMMP) algorithm. EMMP algorithm is greedy and computationally less complex enabling fast SAR image reconstructions. The proposed EMMP based SAR image reconstruction technique also performs autofocus and image reconstruction simultaneously. Based on a variety of metrics, performance of the proposed EMMP based SAR image reconstruction technique is investigated. The obtained results show that the proposed technique provides high resolution images of sparse target scenes while performing highly accurate motion compensation.

1. Introduction

Synthetic Aperture Radar (SAR) is a technique to generate high resolution images of ground reflectivity from a sensor platform. Over more than five decades of their use, SAR systems have found wide variety of application areas ranging from military surveillance to environmental monitoring activities. The success of SAR systems stems from their ability to coherently integrate multiple returns acquired over the course of the flight path of the SAR platforms, which requires precise platform position information within a fraction of the carrier wavelength. Even with the use of modern navigational systems, there is an error due to the difference between actual and the estimated platform positions which results in considerable phase errors especially for high resolution SAR systems typically operating at higher carrier frequencies. Several autofocus techniques have been developed to estimate this residual phase error [1–7]. Once a reliable estimate is obtained, the effect of the phase error is compensated on the raw SAR data to provide better SAR reconstructions.

Compressed Sensing (CS) is a relatively new paradigm [8,9] in which theoretically, sparse signals can be reconstructed by sampling them below Nyquist rate. Application of CS requires the reconstructed signal to be sparse in a known basis [10]. Since sparsity is encountered in many natural signals, CS has found diverse application areas including radar signal processing [11–18]. Compressive sensing based radar in theory has several advantages such as reduced memory size, decreased A/D converter rates or possibility of eliminating the match filtering process [19]. Because CS allows to reconstruct SAR images by using data sampled below the Nyquist rate, the required memory size and A/D converter rate can be relaxed, resulting important cost and complexity savings in practice [20].

In the application of CS to SAR image reconstruction, the scene reflectivity is required to have a sparse representation in a known basis. Speckle noise creates significant challenges in representation of SAR images sparsely. But for radar scenes with highly reflective man-made objects, wavelets [21], standard unit impulse basis

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vectors, or both can be used for a sparse representation of the targets that dominate the scene reflectivity.

SAR image reconstruction by using sparsity driven penalty function has been investigated in [19,22–25]. Ref. [26] gives a thorough survey of recent literature on sparsity driven SAR imaging. CS based SAR imaging is generally formulated as a convex l_1 norm minimization problem and it is solved by either linear programming or greedy pursuit algorithms. Although these techniques do not consider phase errors in SAR image reconstruction, the proposed techniques in [20,27–29] provide sparse reconstructions in the presence of phase errors. However, compared to the commonly used SAR autofocusing techniques, these approaches require significantly more processing time than conventional reconstruction techniques that limits their practical use.

In the present study, a novel SAR reconstruction technique that utilizes a new sparse reconstruction approach called as Expectation Maximization Matching Pursuit (EMMP) algorithm [30] is proposed. The EMMP algorithm uses the compressive measurements as incomplete data about the system and iteratively applies expectation and maximization (EM) steps to construct the complete data that would correspond to a set of SAR data for each dominant target in the scene. The objective of EM iterations is to provide more reliable estimates to the complete data so that accurate and efficient estimation of the individual target parameters can be obtained more reliably in the maximization step. Once, more accurate estimates for a certain target are obtained, its contribution to the incomplete data can be more accurately estimated allowing reconstruction of remaining targets without its interference. This EM procedure also allows to estimate unknown phases for each complete data component in an iterative manner.

The proposed EMMP based SAR imaging algorithm is greedy, computationally less complex, and has lower reconstruction errors compared to l_1 norm minimization. Hence, both the accuracy and convergence rate of the iterations significantly increase, enabling fast and high resolution SAR image reconstructions. Note that, in addition to the preliminary results presented in [31], the proposed approach [32] is extended to conduct autofocus as part of the EMMP iterations. As illustrated on both synthetic and real data sets, the proposed EMMP based SAR reconstruction technique performs highly effective autofocus in the presence of phase errors.

In Section 2, the proposed technique of simultaneous reconstruction and autofocus of sparse SAR images based on EMMP algorithm is described. Section 3 investigates the effect of sparsity parameter on the image reconstruction quality of the proposed technique. Comparison of the image reconstruction performances of the proposed technique and the technique based on the nonlinear conjugate gradient descent algorithm is given in Section 4. Section 5 concludes the article.

2. Simultaneous reconstruction and autofocus of sparse SAR images based on EMMP algorithm

In spotlight mode SAR, an airborne or spaceborne platform carries a mono-static radar system on a straight flight path, while the radar transmits and receives echoes from the area of interest (see Fig. 1). The received and digitized radar returns are coherently processed to obtain significantly higher resolutions in azimuth direction that could have been obtained by a large aperture antenna. Baseband measurement model of a spotlight SAR system can be written as the following vector-matrix equation [25]:

$$\mathbf{y} = \mathbf{G}\mathbf{x} + \mathbf{w}, \tag{1}$$

where $\mathbf{y}$ is the received signal (the measurement vector), $\mathbf{G}$ is the complex valued discrete SAR projection operator matrix, $\mathbf{x}$ is the reflectivity vector and $\mathbf{w}$ is the additive complex white Gaussian measurement noise vector. Assuming that the reconstruction will be performed over a target grid of $N \times N$ range and azimuth samples, then, $\mathbf{y}, \mathbf{x}$, and $\mathbf{w}$ are $m \times 1$ vectors and $\mathbf{G}$ is a matrix of size $m \times m$, respectively, for $m = N^2$.

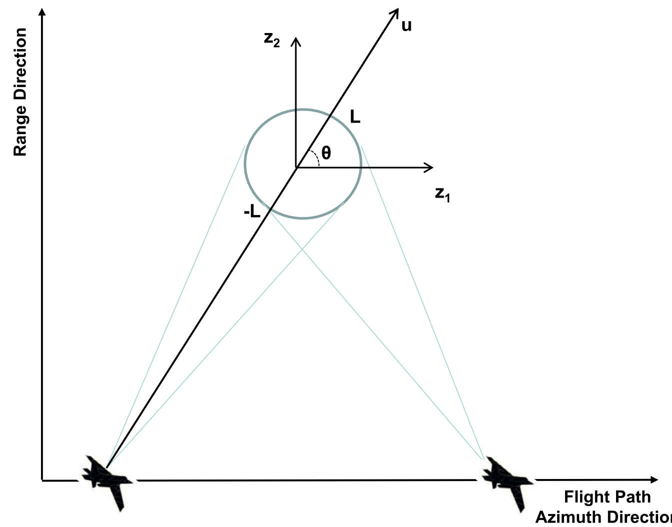

Fig. 1. Spotlight mode SAR imaging geometry.

One important application of SAR systems is imaging of man-made objects. Since, typical reflections from man-made objects are significantly stronger than that of background terrain, reflectivity distribution over the imaged area can be modeled as a sparse distribution over an appropriate set of vectors such as wavelets.

Proven guarantees of CS based reconstruction techniques ensure that reliable reconstruction of a sparse signal of length m is possible if the measurement matrix satisfies Restricted Isometry Property (RIP) and the number of measurements are at least $O(K \log(m/K))$ where K is the level of sparsity of the signal [33], which can be significantly smaller than m. Thus, for sparse SAR image reconstructions, the required number of samples can be significantly lower than the Nyquist rate, providing important hardware savings. To exploit the potential reduction in the sampling rate, the method described in [20] can be used to under-sample the measured data. Assuming that the reflectivity vector is sparse in the column space of a given matrix $\boldsymbol{\Psi}$ with representation coefficients $\boldsymbol{\alpha}$, measurement model given in (1) can be written equivalently as:

$$\mathbf{y} = \mathbf{G}\boldsymbol{\Psi}\boldsymbol{\alpha} + \mathbf{w} = \mathbf{A}\boldsymbol{\alpha} + \mathbf{w}. \tag{2}$$

In CS applications, it is desired to obtain a reconstruction which is as sparse as possible while providing a tolerable fit to measurements. For this purpose, l_0 norm of $\boldsymbol{\alpha}$ can be minimized [8,9]. Since l_0 norm optimization requires combinatoric search that is rarely feasible in practice, generally the l_0 norm problem is relaxed to l_1 norm minimization problem. It is proven that l_0 and l_1 norm minimization problems provide the same solution if $\boldsymbol{\alpha}$ is sparse and $\mathbf{A}$ holds the RIP [34,35].

Generally, the SAR image reconstruction in CS methodology has been formulated in two different approaches. In Basis Pursuit Denoising (BPDN) [36] formulation,

$$\min_{\boldsymbol{\alpha}} \|\boldsymbol{\alpha}\|_1 \quad \text{such that} \quad \|\mathbf{y} - \mathbf{A}\boldsymbol{\alpha}\|_2 \le \sigma, \tag{3}$$

the scene with minimum l_1 norm is reconstructed such that the resulting fit error to measurements is less than a threshold σ. In LASSO formulation [37],

$$\min_{\boldsymbol{\alpha}} \|\mathbf{y} - \mathbf{A}\boldsymbol{\alpha}\|_2 \quad \text{such that} \quad \|\boldsymbol{\alpha}\|_1 \le \tau, \tag{4}$$