Radar Imaging with Sparse Constraint: Principle and Initial Experiment

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Abstract

In this paper, we introduce a radar imaging framework with sparse constraints naming sparse microwave imaging. It is mainly the combination of traditional radar imaging technology and sparse signal processing, achieving benefits in both improving the imaging quality of current systems and designing optimized sparse microwave imaging systems. We proceed several experiments to verify our methodology, including the processing of current SAR raw data with sparse reconstructions algorithm and an airborne experiment with specially designed sparse microwave imaging system. Though there still exist several challenges, experiment results show that for both non-sparse and sparse scenes, our framework works well.

1 Introduction

Modern SAR systems commonly aim at two key features of system performance: wide mapping swath and high imaging resolution. According to the SAR theory, wider swath means a larger observing area i.e. more imaging data; higher resolution requires a wider signal bandwidth, which leads to a higher sampling rate and data amount because of the Nyquist theorem. So, as the swath and resolution increase in modern SAR systems, the system complexity and data amount also increase remarkably, which brings difficulties to the hardware implementation.

Some features of radar imaging, e.g. the sparsity of target scene, could be used to deal with these problems. In many cases, the SAR target scene is sparse, i.e. there only exist a few strong targets in the whole scene. It makes us possible to introduce the sparse signal processing theory to the microwave imaging. Sparse signal processing is developed by mathematicians by the end of 20th century [1]. A main achievement of sparse signal processing is named as compressive sensing (CS) [2, 3]. According to CS, a sparse signal can be reconstructed with much less samples than that required by Nyquist theorem. Many efforts have been done to introduce the sparse signal processing technology to SAR imaging, aiming at benefits including reducing the system complexity and improving the system performance [4, 5, 6].

In this paper, we will mainly introduce our work on radar imaging framework with sparse constraints, naming *sparse microwave imaging* [5]. As a novel concept of radar imaging, sparse microwave imaging is mainly the combination of traditional radar imaging technology and newly developed sparse signal processing theory. In the signal processing stage of sparse microwave imaging systems, the sparse reconstruction algorithm such as ℓ_q $(0 < q \leq 1)$ regularization algorithm is utilized as the signal processing method instead of conventional matched filtering. As the result, it makes us possible to proceed the full-sampled and under-sampled data directly in both range and azimuth directions.

Comparing with traditional radar imaging, sparse microwave imaging not only shows its advantages in improving the performance of current microwave imaging systems e.g. enhancing the image quality including better distinguishing ability, multilook application [12] and reducing the sidelobes and ambiguity (in this way, the sparse microwave imaging only performs as a novel signal processing method), but also in possibility of reducing system sampling rate towards the sparse target scenes such as oceanic targets (it means that as a systematic concept, we are able to design a optimized sparse microwave imaging system under the guidance of sparse microwave imaging theory), which allows us to achieve a wider swath because of the down-sampling in azimuth direction. These results are all verified via theoretical analysis and empirical experiments. But we are also facing several challenges, including the SNR loss brought by down-sampling, the implementation of under-sampling strategy, the huge computing resources required by the sparse reconstruction algorithms, difficulties the image quality evaluation etc.

To overcome these challenges and verify the effectiveness of our methodology, we test the sparse microwave imaging algorithm with several sets of current SAR raw data. We also design an airborne experiment system to test and verify the above-mentioned challenges.

The rest of this paper is organized as follows. In section 2, we will describe the basic model of sparse microwave imaging. The sparse reconstruction algorithm we used in sparse microwave imaging and its accelerated version is introduced in section 3. To explain the effectiveness of our sparse microwave imaging framework, we exploit experiments on current SAR data which is given in section 4, and in section 5 we also perform an airborne experi-

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ment with optimized designed sparse microwave imaging radar. Finally, the conclusions are given in section 6.

2 Model of Sparse Microwave Imaging

2.1 The Mathematical Model

In a general form, The sparse microwave imaging radar system model can be written as [5]

$$y = \mathbf{\Phi}x + N = \mathbf{\Theta}\mathbf{H}\mathbf{\Psi}\alpha + N, \tag{1}$$

where x is the back-scattering coefficients of targets in the scene, y is the echo signal, $\mathbf{\Phi}$ is the measurement matrix of radar system and N is the noise. $\mathbf{\Phi}$ is defined as $\mathbf{\Phi} = \mathbf{\Theta}\mathbf{H}$ with $\mathbf{\Theta}$ being the matrix representing the down-sampling of the radar system, and $\mathbf{H}$ being the the matrix describing the observation of radar. The scene vector x can also be written as $x = \mathbf{\Psi}\alpha$ with $\mathbf{\Psi}$ being a sparse dictionary/basis and α being the sparse expression of x. In most radar applications, it is difficult to find a universal-feasible dictionary. It means we use a identity matrix as $\mathbf{\Psi}$. x can be reconstructed by a sparse reconstruction algorithm via the following optimization problem

$$\hat{x} = \mathbf{\Psi} \cdot \{\arg\min_{\alpha} \|\alpha\|_q \;\text{ s.t. } \|y - \mathbf{\Theta}\mathbf{H}\mathbf{\Psi}\alpha\|_2 \leq \epsilon\}, \tag{2}$$

where $0 < q \leq 1$.

2.2 The Hardware Design

Of course, we can directly inherit a current conventional SAR hardware system and work along with the sparse signal processing methods. While, we more likely to design a optimized sparse microwave imaging system under the guidance of sparse microwave imaging theory. Figure 1 provides a diagram of components of a typical radar system. In this diagram, we can find some potential modifiable blocks which are shown in gray. More details about the sparse microwave imaging model can be found in reference [5].

- The waveform. We can use an alternative radar waveform to achieve optimized measurement matrix. Current widely used chirp signal can still be used in the sparse microwave imaging, while some other waveforms e.g. orthogonal coded signals might lead to a better system performance.

- The A/D sampling. We can apply different sampling strategies e.g. the non-uniform sampling, aiming at a better measuring effectiveness. In our application, we believe that a pseudo-random sampling with definite interval is a reasonable choice.

- The antenna spacial location. We can modify the location of antenna or install antenna array to achieve spatial diversity. We believe that in the DPCA mode, we can at least loose the constraints to the antenna position and platform velocity.

- The antenna footprint. Besides, the platform motion and beam scanning might provide us better sparse reconstructing performance and wider swath. The sparse microwave imaging framework works for most beam scanning modes including ScanSAR and TOPSAR, and the combining of fast beam scanning and under-sampling in azimuth direction can provide us both wide swath and reduction of scalloping effect. Furthermore, with antenna array and orthogonal waveforms, the platform could even be stationary during imaging [10].

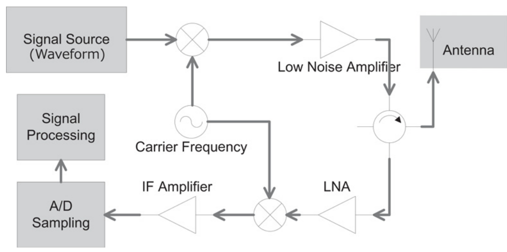

Figure 1: Diagram of components of a radar system. The grayed blocks are potentially modifiable [5].

3 Sparse Reconstruction Algorithm

Many sparse reconstruction algorithms for radar imaging have been presented for the alternation of matched filtering based algorithms. The sparse signal processing method is initially applied to the range compressed data with few modifications to traditional SAR imaging framework. Because it requires preprocessing procedures (i.e., range compression), this kind of method may increase difficulties in system design. The sparse reconstruction algorithm that exploit SAR raw data with no preprocessing is practically feasible in simplifying the radar hardware [5]. Based on such consideration, we present the ℓ_q regularization method which directly uses the under-sampling raw data, constructs the sparse measurement matrix as the dictionary of the echo signal and reconstructs the SAR image using the iterative shrinkage-thresholding algorithm.

$$x^{(k+1)} = f\left(x^{(k)} + \mu\mathbf{\Phi}^T\left(r - \mathbf{\Phi}x^{(k)}\right), \lambda\right), \tag{3}$$

where μ controls the convergence, λ is the regularization parameter, $(\cdot)^T$ denotes the conjugate transpose operation, and $f(\cdot)$ is the shrinkage function. It has high spatial-temporal complexity in time domain.
The computational efficiency of ℓ_q regularization method can be uplifted by decoupling the azimuth and range of the raw data. The concept of decoupling lies in the formation of SAR signal from the reflectivity image of the observation area [7]. The decoupling operator can be implemented by using the principle of conventional algorithms, e.g. range doppler algorithm (RDA) and chirp scaling algorithm (CSA). Here we take CSA as the example. The measurement matrix is viewed as the azimuth convolution $\mathcal{H}_a^T$ imposed on the reflectivity image

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to obtain doppler history, the range-azimuth migration operator $\mathcal{H}_{sc}^{T}$ to generate different curves, and the operator $\mathcal{H}_{bulk\_pc}^{T}$ to complete the azimuth-range coupling and form the echo signal [8].

$$\mathbf{\Phi} \cdot x = \mathbf{\Theta} \odot \mathcal{H}_{sc}^{T} \left\{ \mathcal{H}_{bulk\_pc}^{T} \left\{ \mathcal{H}_{a}^{T} \left\{ x \right\} \right\} \right\}, \qquad (4)$$

where $\odot$ defines the Hadamard matrix product. $\mathcal{H}_{sc}$, $\mathcal{H}_{bulk\_pc}$ and $\mathcal{H}_{a}$ are corresponding to the phase functions in CSA. The computational complexity is reduced from $O\left(N^2\right)$ to $O\left(N\log\left(N\right)\right)$ compared with the non-accelerated ℓ_q regularization method. The accelerated ℓ_q regularization method is effective in the reconstruction for sparse scenes with sub-sampling data. The results on real data also show that the off-grid may not be a problem for sparse microwave imaging. In additional, it can be also applied to process the non-sparse scene with Nyquist-sampling data.
The ℓ_q regularization method is also useful to various scenarios such as displaced phase center antenna (DPCA) [9] and multi-channel SAR imaging.
In a conclusion, first of all, the sparse microwave imaging method based on ℓ_q regularization is feasible for improving the quality of SAR image, with the verification in the real data experiment. Secondly, this method can be accelerated, making it probable to be deployed in processing the existing SAR system. In addition, through the accelerated method it is expected to design more ambitious imaging radar.

4 Experiment with Current Data

To explain the effectiveness of our proposed method and verity its advantages, we test our algorithm with a set of current raw data that achieved from traditional SAR systems. We exploit the sparse microwave imaging method on both sparse and non-sparse scenes [5].
The sparse microwave imaging method can be used to improve the imaging quality of current full-sampled SAR systems. For examples, reducing the sidelobes and the azimuth ambiguity [11], and improving the distinguishing ability. The sparse microwave imaging method leads to successful imaging for non-sparse scene with full-sampled measurements. Some simulations and experiments show that the distinguish ability can me improved with the utilizing of sparse microwave imaging. In our applications, the distinguish ability of typical targets could be improved for a certain extent, but not much. The azimuth ambiguity can also be reduced under the sparse microwave imaging framework. Empirically, compared with the traditional methods, the ambiguity can be reduced over 10dB.

5 Airborne Experiment

Though the signal processing methodology can be successfully exploited with current SAR data, we more likely to design a novel optimized sparse microwave imaging radar. As an initial attempt, we will briefly introduce an airborne experiment that proceeded in September 2013, including the design of radar system and target scene, and an initial result.
We use an airborne experiment to exploit the experiment. The radar works in C-Band (5.6GHz). We select several types of scenes in this experiment. They are all some ideal sparse scenes, including salt pans, islands, harbors, ships and offshore oilfields, located by the seashore of Tianjin, China.

5.1 Initial Result

The experiment is still on-going. An initial result and analysis with phase transit diagrams is given below.
We analyze a typical sparse scene as shown in figure 2.
First, we analyze the imaging performance under different sampling schemes. We use the uniform sampling in figure 3(a) and non-uniform sampling in figure 3(b) with the same sampling rate 60%. The uniform sampling fails to image while the non-uniform sampling successes, which follows the same assertion as the phase transit diagram shown in 4.
Then, we analyze the imaging quality under different sampling rates. A result of 70% sampling is shown in figure 5(a) and a 40% sampling is shown in figure 5(b). As the phase transit diagram suggests in figure 6, 70% under-sampling is enough for sparse reconstruction while 40% under-sampling rate is too low to achieve a successful recovery.

6 Conclusions

In this paper, we present the model and methodology of the sparse microwave imaging. Comparison of the imaging results with that of the traditional scheme leads to the following conclusions. For the full sampling data, sparse microwave imaging can improve the imaging performance, including better distinguish ability, reduction of ambiguity and sidelobes. For the sparse scene, the sparse microwave imaging is feasible for the down-sampled data. More data sets of airborne experiment in Tianjin are still under processing. Further analysis of the experiment data is needed to evaluate the performance of sparse microwave imaging.

(a) An typical sparse scene: salt pans by the seashore.

(b) Initial result of airborne experiment with sparse reconstruction algorithm and full-sampling.

Figure 2: Airborne experiment in Tianjin, China.

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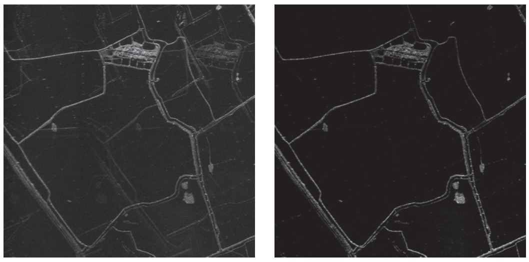


(a) Uniform sampling with sampling rate 60%.
(b) Non-uniform sampling with sampling rate 60%.

Figure 3: Imaging results of different sampling schemes.

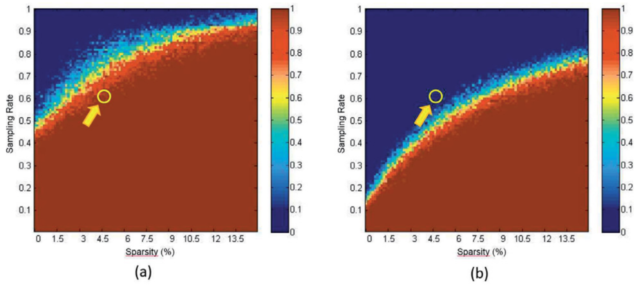
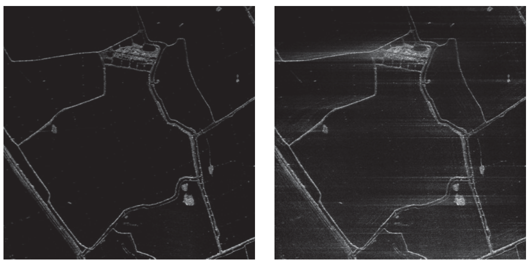


Figure 4: Phase transit diagram of different sampling schemes. Yellow circle is the point that represents the experiment condition. (a) uniform sampling and (b) non-uniform sampling.



(a) Under-sampling rate 70%. (b) Under-sampling rate 40%.

Figure 5: Imaging results of different sampling rates.

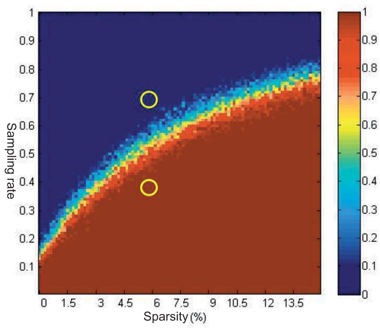


Figure 6: Phase transit diagram of different sampling rates. Yellow circles are the points that represent the different sampling rates.

References

[1] R. Baraniuk, E. Candès, M. Elad, et al: *Applications of sparse representation and compressive sensing*, Proceedings of the IEEE, Vol. 98, pp.906–909, 2010.

[2] D. Donoho: *Compressed sensing*, IEEE Trans. on Information Theory, Vol. 52, pp.1289–1306, 2006.

[3] E. Candès, J. Romberg and T. Tao: *Stable signal recovery from incomplete and inaccurate measurements*, Communications on pure and applied mathematics, Vol. 59, pp.1207–1223, 2006.

[4] J. Ender: *On compressive sensing applied to radar*, Signal Processing, Vol. 90, pp.1402–1414, 2010.

[5] Zhang B., Hong W., Wu Y.: *Sparse microwave imaging: Principles and applications*, Science China Information Science (Series F), Vol. 55, pp.1722–1755, 2012.

[6] S. Samadi, M. Cetin and M. Masnadi-Shirazi: *Sparse representation-based synthetic aperture radar imaging*, IET Radar, Sonar and Navigation, Vol. 5, pp.182–193, 2011.

[7] Fang J., Xu Z., Zhang B., et al: *Fast Compressed Sensing SAR Imaging based on Approximated Observation*, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 7, pp.352-363, 2014.

[8] Jiang C., Zhang B., Fang J., et al: *An efficient lq regularization algorithm with range-azimuth decoupled for sar imaging*, Electronics Letters, Vol. 50, pp.204–205, 2014.

[9] Fang J., Zeng J., Xu Z. et al: *Efficient DPCA SAR imaging with fast iterative spectrum reconstruction method*, Science China Information Science (Series F), Vol. 55, pp.1838–1852, 2012.

[10] Zhang Z., Zhang B., Jiang C., et al: *Influence factors of sparse microwave imaging radar system performance: Approaches to waveform design and platform motion analysis*, Science China Information Sciences (Series F), Vol. 55, pp. 2301–2317, 2012.

[11] Zhang B., Jiang C., Zhang Z., et al: *Azimuth ambiguity suppression for SAR imaging based on group sparse reconstruction*, in Workshop on Compressed Sensing applied to Radar 2013, Germany, 2013.

[12] Fang J. Zhang B., Xu Z., et al: *On Selection of the Observation Model for Multilook Application in Sparse Microwave Imaging*, in European Conference on Synthetic Aperture Radar 2014, Germany, accepted.

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