IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium | 978-1-6654-2792-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/IGARSS46834.2022.9884535

SAR SUPER-RESOLUTION USING PHYSICS-AWARE ADAPTIVE COMPRESSED SENSING

Sanhita Guha [1], Mihai Datcu [2], Joachim Ender [1]
[1] Fraunhofer Institute for High Frequency Physics and Radar Techniques (FHR)
[2] German Aerospace Center (DLR)

ABSTRACT

The resolution requirements of modern radar applications are increasing rapidly and cannot be fulfilled by the limited number of wide-band radar systems. Many approaches have been explored to solve this problem under the topic of super-resolution. In this paper, we propose a hybrid algorithm for resolution improvement, where we aim to combine the adaptability of deep neural networks with the reliability and expertise of traditional domain-specific SAR processing.

***Index Terms*—** ISTA, Learned ISTA, Approximated Observation, SAR Super-resolution,High resolution radar, Algorithm Unrolling, Hybrid Approaches to Super-resolution

1. INTRODUCTION

Compressed Sensing (CS) theory allows the reconstruction of signals sampled much below the Nyquist rate, if the signal is sparse in a certain domain. The sparse representation of a signal can thus be viewed as a map between the low-resolution and high-resolution representations. If this unique sparse representation for a signal can be estimated correctly, compressed sensing techniques can be used to improve the resolution of images obtained from optical and radar systems.

However, the application of CS algorithms to real-world problems is not trivial. Many CS algorithms require well tuned parameters specific to the signal and also suffer from large memory requirements due to the size of the sensing matrices. In order to alleviate some of these issues, deep-learning based CS methods have been developed to learn such parameters adaptively ([1], [2]). But most of the existing research in this direction focuses only on optical images. Another big issue with such deep-learning based approaches is the 'black-box' effect and lack of reproducibility of results. Researchers have been working towards solving this problem by using a hybrid approach where deep-learning networks are combined with domain-specific algorithms. Recent research on 'Physics aware neural networks' and 'Algorithm Unrolling' ([3], [4], [5]) are steps in this direction.

This work aims to combine the advantages of deep-learning, compressed sensing and domain-specific SAR processing. Inspired by the recent efforts in hybrid approaches, a deep-learning based CS method is combined with traditional SAR processing for super-resolution. Many recent works have discussed deep learning for SAR ([6], [7]), but such a hybrid approach for SAR super-resolution has not been widely explored. This algorithm is applicable to real scenes as long as the sparsity constraints are obeyed corresponding to the number of measurements [8]. In this paper, the term 'Physics-aware' specifically points to the SAR processor steps used in Section 3 and 4.

The paper is organized as follows: Section 2 discusses a deep-learning based Iterative Soft Thresholding Algorithm (ISTA) applied to a low resolution SAR image (SAR-ISTA-Net), Section 3 presents an 'Approximated Observation' (AO) algorithm developed for SAR, Section 4 discusses the hybrid approach and presents SAR-ISTA-Net combined with 'Approximated Observation' (SAR-LISTA-AO) for adaptive super-resolution. The paper ends with the conclusion in Section 5.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodoska-Curie grant agreement No 860370.

2. LEARNED ISTA FOR SAR IMAGE SUPER-RESOLUTION

In this section, we try to analyse and apply the results of the network developed for an optical image [9] to a SAR image. Let us consider that a narrow band radar is used to detect a scene, thereby giving a low resolution image. Let $\mathbf{y}$ represent the measurements obtained from this radar. $\mathbf{x}$ denotes the sparse vector of scene reflectivities that has to be estimated. $\mathbf{A}$ denotes the sensing matrix and $\mathbf{n}$ represents the noise.The CS equation is:

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{n} \tag{1}$$

A popular compressed sensing algorithm called Iterative Soft-Thresholding Algorithm (ISTA) [10] can be used to estimate $\mathbf{x}$ in this framework. The two main update steps of ISTA are expressed as follows:

$$\mathbf{r}^{(\mathbf{it})} = \mathbf{x}^{(\mathbf{it-1})} - \rho^{(it)}\mathbf{A}^{\mathbf{H}}(\mathbf{A}\mathbf{x}^{(\mathbf{it-1})} - \mathbf{y}) \tag{2}$$

$$\mathbf{x}^{(\mathbf{it})} = \underset{x}{\operatorname{argmin}} \frac{1}{2}\|\mathbf{x} - \mathbf{r}^{(\mathbf{it})}\|_2^2 + \lambda\|\psi\mathbf{x}\|_1 \tag{3}$$

Here, ψ is the sparsifying basis, ρ is the step-size, $\mathbf{r}$ represents the residual obtained from the previous iteration. Eqn. (3) denotes the proximal-mapping of the residual $\mathbf{r}$ and λ is the associated threshold.

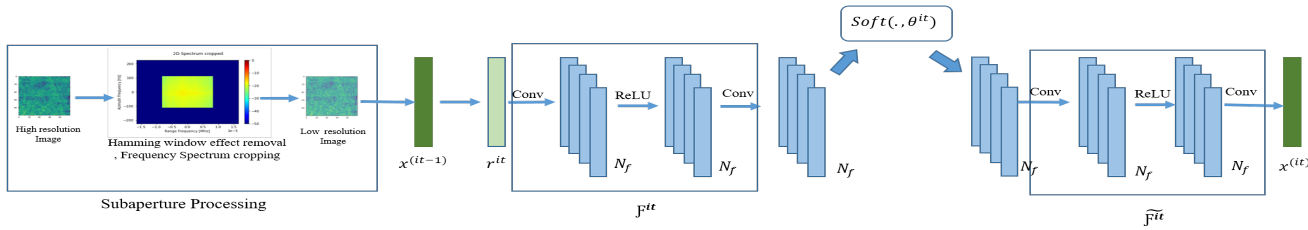

Fig. 1: SAR-ISTA-Net Algorithm

In [9], the sparsifying transform ψ is replaced by $\mathcal{F}(.)$ which consists of 2 convolution operators and a ReLU operator. Based on Theorem 1 of [9], the eqn. (3) becomes

$$\mathbf{x}^{(\mathbf{it})} = \underset{x}{\operatorname{argmin}} \frac{1}{2} \|\mathcal{F}(\mathbf{x}) - \mathcal{F}(\mathbf{r}^{(\mathbf{it})})\| + \theta \|\mathcal{F}(\mathbf{x})\| \tag{4}$$

The conventional ISTA algorithm is unrolled into a deep network where each block corresponds to an iteration of the ISTA. The SAR-ISTA-Net architecture is shown in Fig.1. ψ, ρ, and shrinkage threshold θ are all learned as parameters of the network.

In this paper, the SAR-ISTA-Net is applied to TerraSAR-X data in spotlight mode acquired from Delhi, India. In general, the resolution of a SAR image cannot be improved without additional information. However, in most practical cases, the scene reflectivity can be assumed to be sparse. Using such a sparsity assumption, CS methods can be applied to obtain significant resolution improvement.

2.1. Pre-processing of TerraSAR-X scene

A low resolution version of the TerraSAR-X data—as shown in Fig 2— is obtained by sub-aperture processing and this image is used to test the super-resoluton capabilities of the ISTA-Net. A range-azimuth frequency spectrum is first obtained from the complex data. The 2D-spectrum is then divided by the hamming window and one-fourth of the frequency spectrum is cropped from the center. The image obtained from this cropped spectrum has a significant missing frequency component, and therefore, a much lower resolution.

2.2. Network Parameters

The network was trained with image pairs of size 33x33. The Adam optimizer was used with a learning rate of 0.001. 9 layers were used and a batch size of 16 was used for the current implementation.

Fig 3 shows the image obtained from the SAR-ISTA-Net. There is a noticable enhancement of the scatterers with respect to the background as compared to the low resolution image.

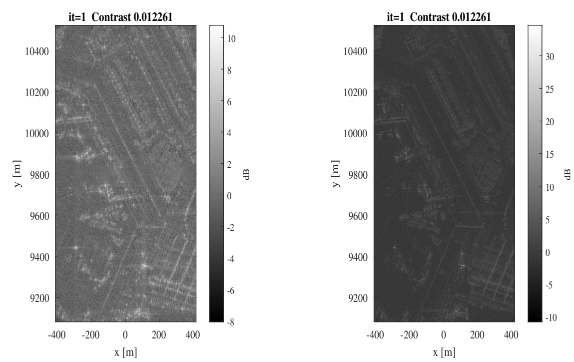

Fig. 2: (a) Low Resolution Image. (b) Ground truth.

3. APPROXIMATED OBSERVATION FOR SAR

In this section, we discuss an approach to SAR image super-resolution using an ISTA-based compressed sensing algorithm called 'Approximated Observation'.

In [11], this idea was presented for a SAR stripmap mode with undersampled data. Here, we apply it to the super-resolution problem. The SAR Approximated Observation workflow is presented in Fig 4, 5. In terms of eqn.(2), $\mathbf{A^H}$ is the traditional 'SAR processor' and $\mathbf{A}$ is the measurement simulator or 'Inverse-SAR-Processor'.

The algorithm is briefly described as follows: We start with a low resolution SAR image $\hat{x}$ from a narrow band radar. This image goes through the soft thresholding step of the ISTA algorithm and is then sent to the 'Inverse-SAR-Processor'. The inverse SAR processor consists of a series of steps which produces the interpolated SAR measurement $\hat{y}$ from the low resolution image. The difference between the original and interpolated SAR measurements then goes to the SAR processor. The SAR processor returns an image with improved resolution shown in Fig 6. The interpolation step in the workflow along with the ISTA step are responsible for the resolution improvement of the original image.

This algorithm combines the traditional SAR processing steps with a popular compressed sensing algorithm to achieve super-resolution. However, the parameters of the ISTA step such as the threshold and step-size are very important for the success of this approach. These parameters can be adjusted through trial and error by studying the reconstructed SAR im-

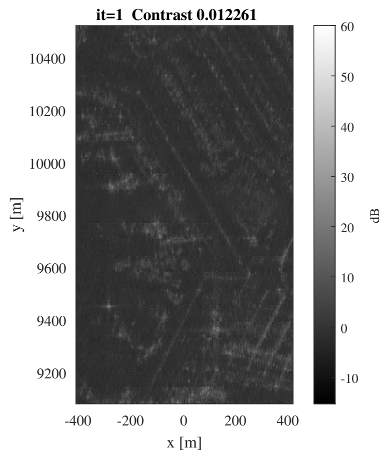

Fig. 3: Result from SAR-ISTA-NET

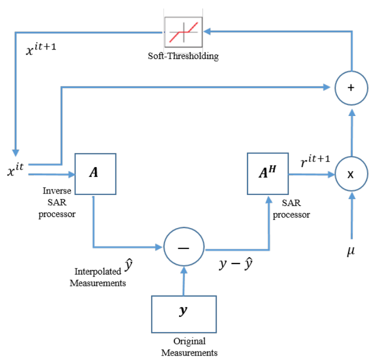

Fig. 4: Approximated Observation Algorithm

ages, but this is non-optimal and non-adaptive.

In order to make this algorithm more adaptive, we propose to use a learned ISTA in combination with the 'Approximated Observation' approach. This is the main contribution of the paper and is discussed in the following section.

4. LEARNED ISTA WITH APPROXIMATED OBSERVATION

In Section 2, convolutional operators were used to adaptively determine the sparsifying transform ψ, but the sensing matrix $\mathbf{A}$ was kept fixed. In Section 3, the sensing matrix is more adaptive to the image generation process but the parameters of of the ISTA-step are difficult to tune.

Now, we combine the two methods and Fig 7 shows the proposed algorithm. The ISTA-step is replaced by SAR-ISTA-Net and the residual connects the two parts. Fig 8 is obtained after one iteration of the hybrid algorithm.

Table 1 shows the mean-squared-error (MSE), peak-signal-to-noise-ratio (PSNR), and the structural-similarity-index (SSIM) between the ground truth and the results obtained from the three algorithms. Fig 9 shows the range

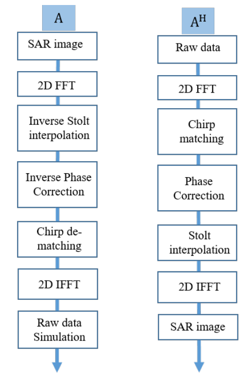

Fig. 5: Approximated Observation -SAR and Inverse SAR Processor

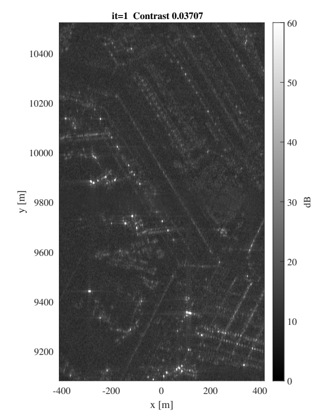

Fig. 6: Result from Approximated Observation

profile of an image segment for all three algorithms. The Approximated Observation algorithm performs much better than the others but this comes at the cost of adaptibility. The SAR-LISTA-AO algorithm performs better than the SAR-ISTA-Net for all the three metrics. This shows that the hybrid approach can provide the necessary trade-off between reliable performance and adaptibility.

5. CONCLUSION

In this paper we explore a novel hybrid-approach for the super-resolution of SAR images. A hybrid CS algorithm combining the advantages of a deep-learning network and a

Table 1: Performance Parameter

	MSE	PSNR	SSIM
SAR-ISTA-Net	0.057	12.466	0.301
AO	0.009	20.017	0.648
SAR-LISTA-AO	0.048	13.181	0.386

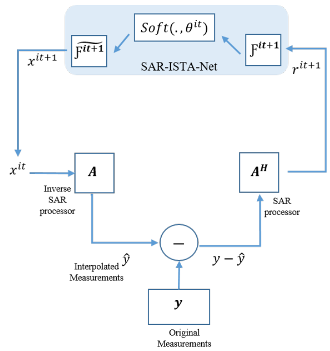

Fig. 7: Learned ISTA based Approximated Observation for SAR-basic block

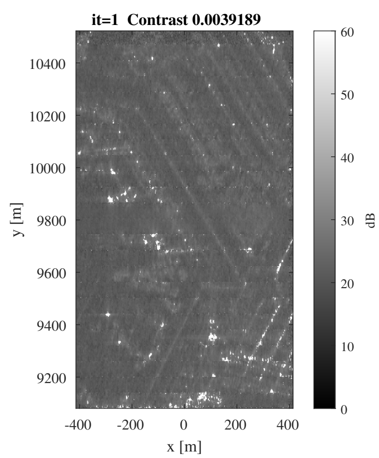

Fig. 8: Result from Learned ISTA based Approximated Observation Algorithm

traditional SAR processor is implemented.

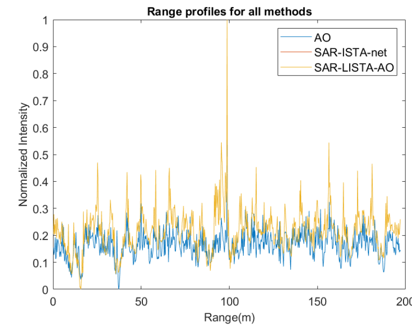

Fig. 9: Range Profile

6. REFERENCES

[1] Chu He, Longzhu Liu, Lianyu Xu, Ming Liu, and Mingsheng Liao, "Learning based compressed sensing for sar image super-resolution," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 5, no. 4, pp. 1272–1281, 2012.

[2] Biao Hou, Kang Zhou, and Licheng Jiao, "Adaptive super-resolution for remote sensing images based on sparse representation with global joint dictionary model," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 4, pp. 2312–2327, 2018.

[3] Vishal Monga, Yuelong Li, and Yonina C. Eldar, "Algorithm unrolling: Interpretable, efficient deep learning for signal and image processing," *IEEE Signal Processing Magazine*, vol. 38, no. 2, pp. 18–44, 2021.

[4] Suhas Lohit, Dehong Liu, Hassan Mansour, and Petros T. Boufounos, "Unrolled projected gradient descent for multi-spectral image fusion," in *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019, pp. 7725–7729.

[5] Samira Pakravan, Pouria A. Mistani, Miguel A. Aragon-Calvo, and Frederic Gibou, "Solving inverse-pde problems with physics-aware neural networks," *Journal of Computational Physics*, vol. 440, pp. 110414, 2021.

[6] Zhongling Huang, Mihai Datcu, Zongxu Pan, and Bin Lei, "Deep sar-net: Learning objects from signals," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 161C, pp. 179–193, 01 2020.

[7] Xiaoxiang Zhu, Sina Montazeri, Mohsin Ali, Yuansheng Hua, Yuanyuan Wang, Lichao Mou, Yilei Shi, Feng Xu, and Richard Bamler, "Deep learning meets sar: Concepts, models, pitfalls, and perspectives," *IEEE Geoscience and Remote Sensing Magazine*, pp. 0–0, 2021.

[8] Simon Foucart and Holger Rauhut, *A Mathematical Introduction to Compressive Sensing*, Springer New York, New York, NY, 2013.

[9] Jian Zhang and Bernard Ghanem, "Ista-net: Interpretable optimization-inspired deep network for image compressive sensing," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2018, pp. 1828–1837.

[10] I. Daubechies, M. Defrise, and C. De Mol, "An iterative thresholding algorithm for linear inverse problems with a sparsity constraint," *Communications on Pure and Applied Mathematics*, vol. 57, no. 11, pp. 1413–1457, 2004.

[11] J. Fang, Z. Xu, B. Zhang, W. Hong, and Y. Wu, "Fast compressed sensing sar imaging based on approximated observation," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 7, no. 1, pp. 352–363, Jan 2014.