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Special Topic: Large Model-Driven Aerospace Microwave Imaging

Adaptively regularized SAR imaging network with efficient unfolding

Shiping FU[1], Yufan CHEN[1], Zhe ZHANG[1,2*] & Qixiang YE[1]

[1]*School of Electronic, Electrical and Communication Engineering, University of Chinese Academy of Sciences, Beijing 101408, China*
[2]*Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China.*

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Synthetic aperture radar (SAR) is a widely used microwave imaging technique for earth observation thanks to its all-weather and high-resolution capabilities [1].

In the past decades, sparse SAR imaging based on compressed sensing (CS) has enabled reconstruction from undersampled data while suppressing sidelobes and ambiguities [2]. To mitigate the high computational complexity of CS algorithms, approximated observation operators derived from matched filters have been adopted. However, these hand-crafted operators often lack adaptability to scenes with varying sparsity levels, limiting their generalizability.

To conquer this limitation, deep unfolding networks (DUNs) [3] have emerged as a promising solution, combining the interpretability of model-based optimization with data-driven deep neural networks. By mapping conventional solvers into deep architectures, DUNs achieve improved imaging performance. Nevertheless, the baseline DUNs still struggle with scene generalization due to the empirically designed priors. Furthermore, many existing frameworks are constrained by time-consuming matrix inversion operations, which limit their efficiency in 2D signal processing. Consequently, there is a critical need for efficient alternatives that avoid matrix inversion while maintaining reconstruction quality.

In this study, we propose ARSAR-Net, an adaptively regularized SAR imaging network with high computational efficiency. By incorporating a learnable regularizer, ARSAR-Net updates conventional priors to general knowledge for better scene generalization capacity. In practice, the vanilla ARSAR-Net is built upon an ADMM algorithm with linear approximation, which avoids matrix inversion and thereby breaks inherent structural limitations. These advancements establish a new paradigm for efficient and scene-adaptive SAR imaging systems with superior imaging quality [4]. Code is available at the website[1)].

Efficient ADMM for SAR imaging. The SAR imaging mechanism establishes a mathematical relationship between the spatial scattering matrix and the echo matrix, which are vectorized as $\boldsymbol{x}$ and $\boldsymbol{y}$ and linked by an observation matrix $\boldsymbol{\Phi}$, given by $\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{x}$. However, this vectorization-based representation leads to a massive computational cost: the dimensionality of $\boldsymbol{\Phi}$ scales quadratically with the number of pixels ($N^2 \times N^2$), imposing high storage and memory demands.

To solve this issue, the matched filter method [5] approximates the high-dimensional matrix $\boldsymbol{\Phi}$ using efficient 1D operators along the azimuth and range directions. By leveraging these CSA-based operators, the large observation matrix is replaced by a lightweight forward operator $\mathcal{G}(\cdot)$. Within this framework, the scattering coefficient matrix $\boldsymbol{X}$ is reconstructed through the alternating direction method of multipliers (ADMM), a robust optimization algorithm widely used in regularized reconstruction. Through ADMM, the problem is decomposed into two separable subproblems involving $\boldsymbol{X}$ and an auxiliary variable $\boldsymbol{Z}$:

$$\min_{\boldsymbol{X}} \|\mathcal{G}(\boldsymbol{X}) - \boldsymbol{Y_d}\|_2^2 + \lambda\phi(\boldsymbol{Z}) \quad \text{s.t. } \boldsymbol{Z} = \boldsymbol{X}, \tag{1}$$

where λ is the regularization factor and ϕ is a transition function.

However, since $\mathcal{G}(\cdot)$ involves matrix multiplications and Hadamard products, its computation remains costly. Consequently, the explicit update for $\boldsymbol{X}$ cannot be derived through direct matrix inversion.

To avoid the complex matrix inversion, we apply a second-order Taylor expansion to the objective function at $\boldsymbol{X}^{(k-1)}$ where k is the iteration number. By approximating the Hessian matrix with a Lipschitz constant L, we derive the gradient-based update in (2a), where $\rho_n = \rho/L$ is the normalized penalty and $\mu = 2/L$ is the step size. This replaces the computationally expensive matrix inversion with a faster first-order update.

For the $\boldsymbol{Z}$-subproblem, we use a nonlinear proximal operator $\mathcal{F}_\Theta(\cdot)$ parameterized by Θ as the regularization (2b). It can be implemented as either a model-based denoiser or a neural network for noise suppression and image enhancement. Finally, the dual variable $\boldsymbol{V}$ is updated in (2c) to enforce the constraint. The complete iterative process is summarized as follows:

$$\begin{aligned}
\boldsymbol{X}: \quad \boldsymbol{X}^{(k)} &= (1-\rho_n)\boldsymbol{X}^{(k-1)} + \mu\mathcal{T}\left[\boldsymbol{Y_d} - \mathcal{G}(\boldsymbol{X}^{(k-1)})\right] \\
&\quad + \rho_n\left(\boldsymbol{Z}^{(k-1)} - \boldsymbol{V}^{(k-1)}\right), && \text{(2a)} \\
\boldsymbol{Z}: \quad \boldsymbol{Z}^{(k)} &= \mathcal{F}_\Theta\left(\boldsymbol{X}^{(k)} + \boldsymbol{V}^{(k-1)}\right), && \text{(2b)} \\
\boldsymbol{V}: \quad \boldsymbol{V}^{(k)} &= \boldsymbol{V}^{(k-1)} + \boldsymbol{X}^{(k)} - \boldsymbol{Z}^{(k)}. && \text{(2c)}
\end{aligned}$$

* Corresponding author (email: zhangzhe01@aircas.ac.cn)
1) github.com/ShipenFyu/ARSAR-Net.

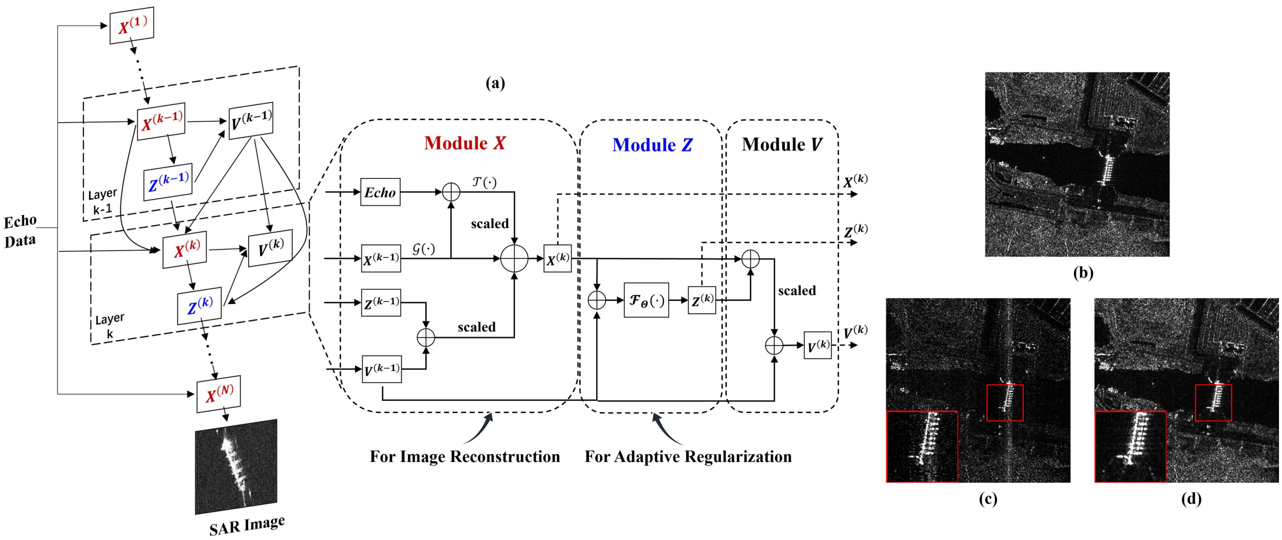

Figure 1 (Color online) ARSAR-Net with imaging results. (a) The unfolding network architecture of ARSAR-Net; (b) ground-truth; (c) conventional imaging result; (d) ARSAR-Net imaging result, which is more consistent with the ground-truth.

ARSAR-network. Based on the iterative steps defined in (2a)–(2c), we design an unfolding network for SAR imaging, where each layer corresponds to one ADMM iteration. The network takes the 2D echo data $\boldsymbol{Y_d}$ as input and produces the scattering coefficient matrix $\boldsymbol{X}^{(N)}$ through N_s cascaded layers, as shown in Figure 1(a). To handle complex-valued matrices within standard deep learning frameworks, each complex-valued input is decomposed into real and imaginary channels before being processed by the nonlinear proximal operator $\mathcal{F}_\Theta$ and then recombined. $\mathcal{F}_\Theta$ is implemented using convolutional layers for feature extraction, activation functions for nonlinear mapping, and normalization layers for training stability[2)].

To accommodate different requirements in terms of computational cost and imaging quality, we provide two variants of ARSAR-Net. ARSAR-Net Swift leverages a multi-scale pyramid structure to minimize computational overhead for real-time inference. In contrast, ARSAR-Net Pro adopts a symmetric architecture with skip-connections to ensure high-fidelity reconstruction and detail preservation.

Experiments in real scenarios. Experiments are conducted using GaoFen-3 satellite data across diverse scenarios including oceans, harbors, and cities. To test the model's generalization capability given limited training data, we apply a random downsampling matrix to the echo signals, creating azimuth-downsampled data at 50% and 75% rates for evaluation.

In real-world tests, ARSAR-Net consistently outperforms conventional regularization and existing deep learning baselines. At 50% sampling, the ARSAR-Net Pro variant achieves a PSNR of 30.75 dB, with 3 dB improvement over standard imaging and showing superior adaptability to both sparse and non-sparse scenes. While the Swift variant reaches a high imaging speed of 67.60 items/s, the Pro version ensures maximum image fidelity and structural consistency, as shown in Figures 1(b) and (c).

Both variants reach an optimal performance-speed trade-off at 9 layers. Convergence analysis shows that the proposed ARSAR-Net model achieves lower training loss and higher stability compared to other networks. These results confirm that the proposed strategy without matrix inversion can effectively balance computational efficiency with imaging quality.

Conclusion. In this study, we proposed ARSAR-Net, an efficient unfolding network with adaptive regularization designed for scene-agnostic SAR imaging. By integrating a learnable regularizer into an unfolding network, ARSAR-Net enables adaptive, data-driven reconstruction across diverse and complex scenes. Built upon the efficient ADMM framework without matrix inversion, ARSAR-Net achieves high computational efficiency. To further meet application-specific needs, two variants of ARSAR-Net were introduced: ARSAR-Net Swift for accelerated imaging and ARSAR-Net Pro for high-fidelity reconstruction. Extensive experiments on both simulated and real SAR datasets validate the effectiveness of our approach, demonstrating significant gains in speed, image quality, and scene adaptability. ARSAR-Net provides a robust and efficient solution for high-quality SAR imaging in complex, real-world scenes.

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2) Please refer to https://arxiv.org/html/2506.18324v1 for the detailed implementation of ARSAR-Net.