Compressive Stripmap SAR Imaging via Sparsity and Smoothness Regularization

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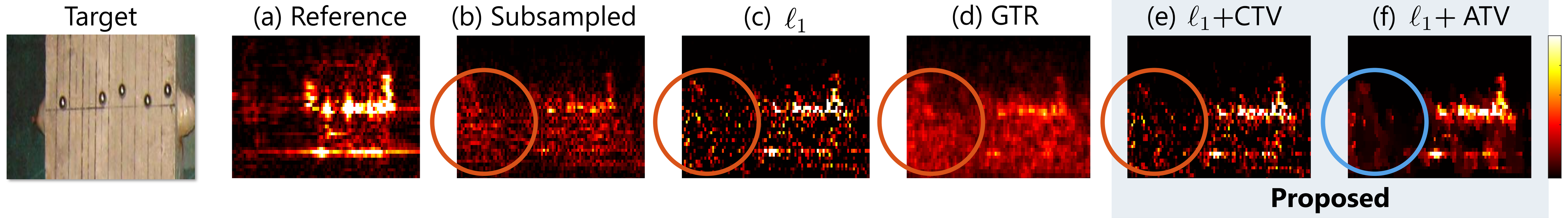
Abstract

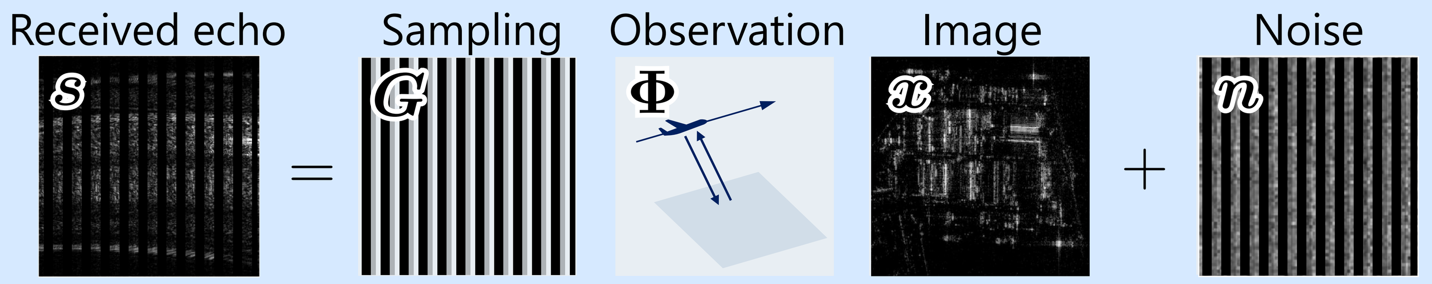
- We propose a SAR image reconstruction method for subsampled signals by combining sparsity and smoothness regularizations.
- The proposed method suppresses aliasing and grainy artifacts while preserving small, high-intensity scatterers.
- Experiments on simulated and real SAR data show that the proposed method achieves lower errors than conventional methods.

Reconstructed Images from Real Data



Compressive Stripmap SAR Imaging

Approximate Observation Model [1]



To reduce the computational cost, we use the inverse of an imaging process (e.g., ω-k) as Φ. This approximation introduces modeling errors, making the reconstruction more difficult.

Optimization Problem

$$\min_{x\in\mathbb{C}^N} \frac{1}{2}\|G\Phi x - s\|_2^2 + r(x)$$

Data fidelity term: enforces consistency between the predicted observation $G\Phi x$ and the measured signal s.

Regularization term: imposes image priors such as sparsity and spatial smoothness.

Sparsity-promoting regularization [2], [3]

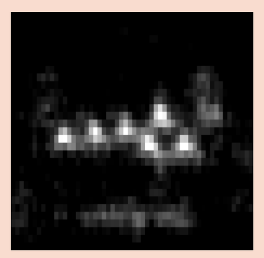
Most components of the image are zero (e.g., ℓ_1-norm regularization).

○ Suppress artifacts, preserve strong scatterers

× Enhance noise, remove weak scatterers

Smoothness-promoting regularization [4]

Neighboring pixels in the image have similar values (e.g., Total Variation (TV) regularization).



○ Suppress noise, preserve edges

× Leave artifacts, remove small scatterers

Proposed Method

Optimization problem

$$\min_{x\in\mathbb{C}^N} \frac{1}{2}\|G\Phi x - s\|_2^2 + \lambda_1\|x\|_1 + \lambda_2 R_{\mathrm{TV}}(x)$$

λ_1, λ_2 : regularization parameters

ℓ_1-norm promotes sparsity

TV promotes smoothness

By combining the two regularization terms, the proposed method suppresses artifacts while preserving small scatterers.

Algorithm

The proposed algorithm is derived by applying primal-dual splitting method (PDS) to the optimization problem.

Two Types of TV for Complex-Valued Images

For complex-valued images, TV can be defined using either complex-valued differences or amplitude differences.

Complex TV (CTV): Penalizing complex-valued differences promotes spatial smoothness in both amplitude and phase.

$$\mathrm{CTV}(x) = \sum_{i=1}^{N}\sqrt{|x_{i+1}-x_i|^2 + |x_j - x_i|^2}$$

Amplitude TV (ATV) [4]: Penalizing amplitude differences promotes stronger smoothness in amplitude.

$$\mathrm{ATV}(x) = \sum_{i=1}^{N}\sqrt{(|x_{i+1}|-|x_i|)^2 + (|x_j|-|x_i|)^2}$$

Experiments

Compared Methods

Proposed Methods
- ℓ_1 + CTV
- ℓ_1 + ATV

Conventional Methods
- Sparsity-promoting: ℓ_1 [2], IHT [3]
- Smoothness-promoting: GTR [4], ATGV [4]

GTR: generalized Tikhonov regularization
ATGV: amplitude total generalized variation

Parameters for SAR Imaging

Parameter	Synthetic Data	Real Data
R_0 (m)	40.6	2.21
Center frequency (GHz)	33.0	32.0
Frequency bandwidth (GHz)	9.82	14.0
Synthetic aperture length (m)	6.03	1.61
Squint angle (°)	0	0
Number of frequency points	301	412
Number of antenna positions	88	67

Experimental Settings

- Uniform azimuth sampling: 1 out of every 4 samples
- Regularization parameters: best values selected through preliminary experiments

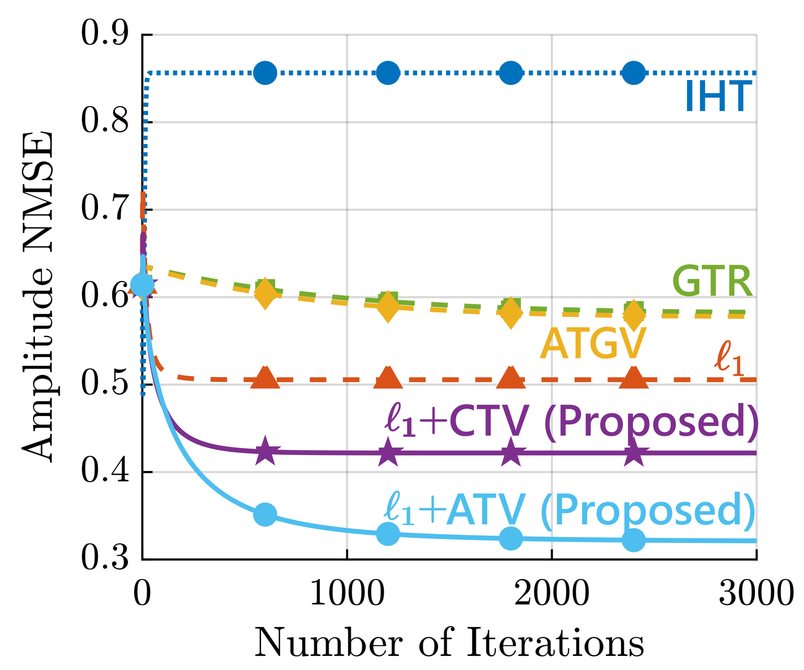
Synthetic Data
- Ground-truth image x: the SAR image provided as the PALSAR-3 sample product (© JAXA)
- Observed signal s: generated by computer simulation

Real Data
- Observed signal s: obtained by computationally subsampling the fully sampled measurement data
- Fully sampled measurement data:
  - Measurement environment: microwave anechoic chamber
  - Measurement system: ground-based SAR
  - Target: metal sphere on a concrete block
- Reference image: reconstructed from the fully sampled SAR measurement data

Experimental Results

- The proposed method achieves the lowest reconstruction error.
- The proposed method suppresses aliasing and grainy artifacts more effectively than the conventional methods.
- It also preserves small, high-intensity scatterers that are removed by overly smooth reconstructions.

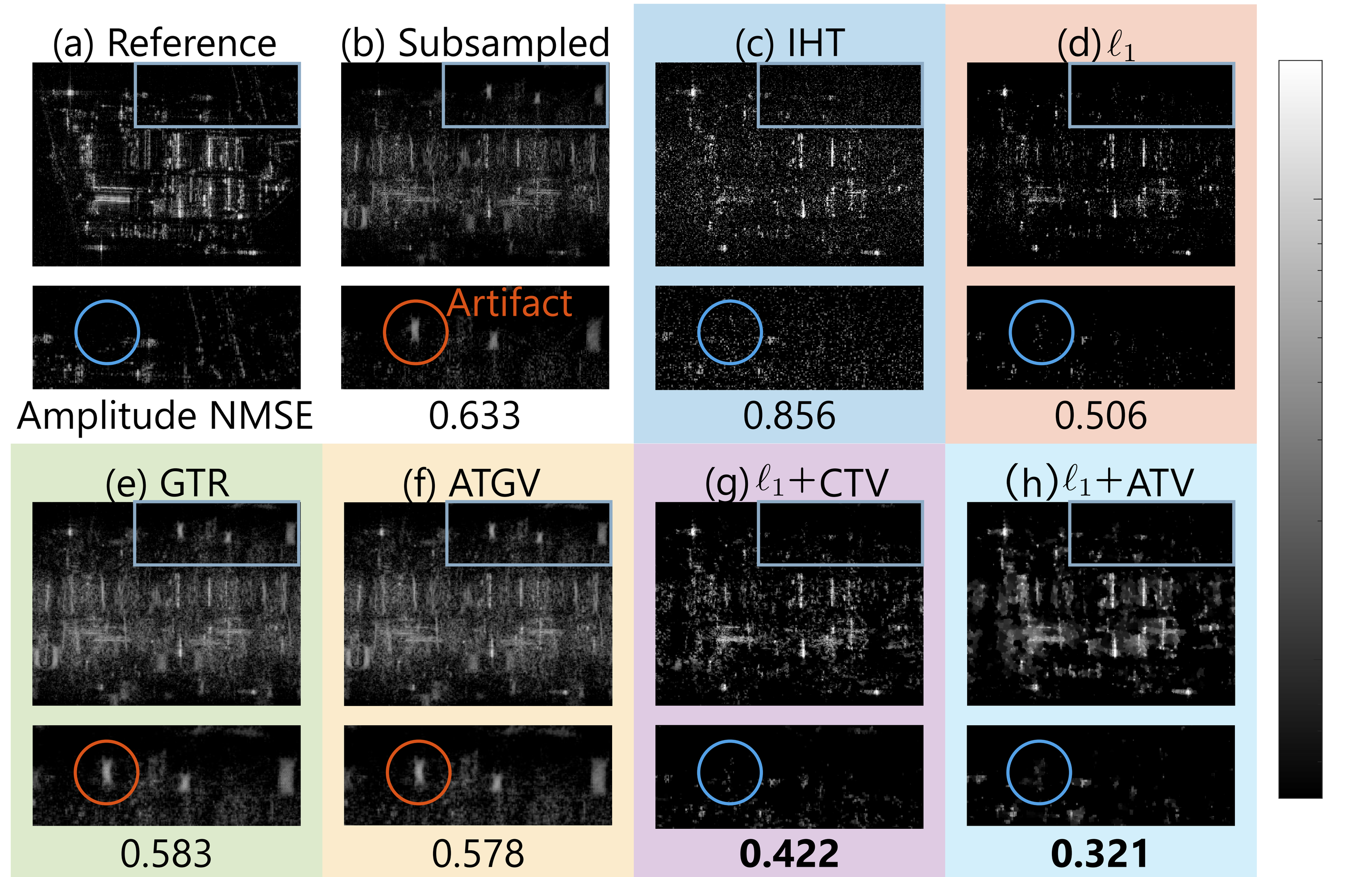
Amplitude NMSE from Synthetic Data



Amplitude NMSE

$$\frac{\|\bar{x} - \bar{x}_{\mathrm{ref}}\|_2^2}{\|\bar{x}_{\mathrm{ref}}\|_2^2} \qquad \bar{x} := |x| \qquad \bar{x}_{\mathrm{ref}} := |x_{\mathrm{ref}}|$$

Reconstructed Images from Synthetic Data



Future Work

- Design regularizers that better distinguish remaining artifacts from true targets.
- Evaluate the proposed method using satellite and airborne SAR data.

Acknowledgment

The PALSAR-3 sample product used for the synthetic data was provided by the Japan Aerospace Exploration Agency (JAXA).

[1] J. Fang, Z. Xu, B. Zhang, W. Hong, and Y. Wu, "Fast compressed sensing SAR imaging based on approximated observation," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 7, no. 1, pp. 352–363, 2014.
[2] T. Hoshino, K. Suwa, Y. Yokota, and T. Hara, "Experimental study of compressive sensing for synthetic aperture radar on sub-Nyquist linearly decimated array," in Proc. IEEE IGARSS, 2019, pp. 831–834.
[3] B. Dong, G. Li, and Q. Zhang, "High-resolution and wide swath imaging of spaceborne SAR via random PRF variation constrained by the coverage diagram," IEEE TGRS, vol. 60, pp. 1–16, 2022.
[4] F. M. Watson, J. Hellier, and W. R. B. Lionheart, "On regularisation of coherent imagery with proximal methods," Inverse Problems, vol. 41, no. 6, p. 065005, 2025.