Physics-Guided Residual-Aware Consensus Equilibrium for SAR Image Despeckling

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***Abstract*—Synthetic Aperture Radar (SAR) image despeckling is a challenging problem due to the multiplicative nature of speckle noise and the need to balance noise reduction with preservation of fine structural details in images. Most of the existing despeckling algorithms aim to solve a composite optimization problem where a data term is regularized by a variety of handcrafted priors. However, such a composite optimization problem often forces a rigid coupling between different components of a model and makes it difficult to incorporate advanced regularization models in a flexible manner. To overcome this problem, a consensus equilibrium (CE) framework is proposed for SAR image despeckling in the multiplicative domain. Specifically, the proposed CE framework views image despeckling as an equilibrium among a variety of complementary operators, including a data fidelity operator based on a physical model of speckle noise and a plug-and-play prior operator for image structural preservation. An equilibrium among these operators is achieved by an iterative fixed-point algorithm without explicitly solving any optimization problem. Experiments with benchmark SAR images show that the proposed CE framework is effective in speckle reduction and image structural preservation. Quantitative comparisons with both reference-based and no-reference image quality metrics confirm the efficacy of the proposed method in terms of speckle suppression and structural preservation.**

***Index Terms*—SAR, speckle, despeckling, sparse regularization, deep denoiser prior, prior-consistent reconstruction.**

I. Introduction

Synthetic Aperture Radar (SAR) images play a significant role in remote sensing owing to their ability to provide images in all weather conditions. However, SAR images are inherently corrupted by speckle noise caused by coherent interference of backscattered signals. This multiplicative noise produces granular fluctuations that degrade image quality and hinder subsequent analysis [1]. To mitigate speckle noise, numerous SAR despeckling methods have been developed, including transform-domain and nonlocal filtering techniques, as well as recent deep learning-based approaches. While learning-based methods show strong performance, purely data-driven models may introduce artifacts due to limited structural constraints. In this work, we propose a consensus equilibrium (CE) framework for SAR image despeckling in the multiplicative domain, where despeckling is formulated as an equilibrium between a physics-consistent Gamma-likelihood data fidelity operator and a plug-and-play denoising prior. The equilibrium is solved using an iterative fixed-point scheme, enabling effective speckle suppression while preserving structural details.

A. Related Works

Recent SAR despeckling techniques can broadly be categorized into three directions: transform-domain and nonlocal filtering approaches, deep learning-based restoration methods, and hybrid optimization frameworks integrating learned priors.

Transform domain and nonlocal sparse based methods: Transform domain filtering approaches along with nonlocal filtering approaches are some of the significant benchmarks for despeckling SAR images. Some of the notable approaches in this category are NL-SAR, which uses patch similarity along with statistical speckle modeling to provide efficient image despeckling results [2], and MuLoG, which provides an efficient tool for advanced image denoising by transforming multiplicative noise to additive noise [3]. In addition to this, low-rank image representation along with sparse representation has been employed to despeckle images while preserving image details [4].

Deep learning-based methods: The development of deep learning methods has remarkably improved despeckling in SAR images. CNN-based methods have been found to achieve better despeckling results compared to traditional filters [5]. Recent self-supervised despeckling methods, such as Speckle2Void, have been developed to address the lack of ground truth images. This enables despeckling from noisy images [6]. Recent works have been dedicated to exploiting attention-based CNNs, transformers, and diffusion-based GANs to learn contextual information from images to improve despeckling results [7], [8].

Hybrid optimization and PnP based frameworks: Hybrid frameworks leverage the interpretability of model-based approaches along with the representation power of deep learning. Plug-and-play (PnP) approaches leverage the integration of learned denoisers within iterative optimization algorithms [9]. This provides flexible integration of powerful priors in a consistent manner with observation models [10]. Recent works have explored further integration of sparse modeling with deep learning, self-supervised, and contrastive learning approaches. Moreover, deep unfolding approaches leverage the integration of iterative optimization along with neural

networks. This provides interpretable and effective frameworks for SAR image restoration tasks [11], [12], [13].

B. Research Gap

Despite the significant progress in despeckling SAR images, there are several limitations in existing despeckling methods. In transform domain and nonlocal filtering methods, structural redundancy and patch similarity are leveraged to reduce speckle noise in SAR images [2], [3]. In sparse and low-rank models, SAR image structures are represented using handcrafted models. However, existing despeckling methods may not effectively represent complex SAR image statistics due to the use of predefined transforms. Deep learning-based despeckling methods have shown promising results in despeckling SAR images by learning effective priors from data. However, existing deep learning-based despeckling methods are purely data-driven and may not effectively incorporate structural constraints in SAR images. In hybrid despeckling methods, the learned denoiser is integrated within optimization schemes. However, in existing hybrid despeckling methods, the learned denoiser may not effectively incorporate structural constraints in SAR images.

C. Motivation and Contributions

In light of this, this paper proposes a consensus equilibrium (CE) framework for SAR image despeckling in the multiplicative domain. This approach to image despeckling is based on an equilibrium between complementary operators, rather than a composite objective function minimization approach. Specifically, a data fidelity operator based on a physical model of the Gamma likelihood is paired with a plug-and-play denoising prior, and their consensus is achieved via an iterative fixed point algorithm. The contributions of this paper are outlined in the following:

1) A consensus equilibrium formulation is presented for SAR image despeckling, offering a flexible alternative to optimization-based approaches to image restoration.
2) A multiplicative domain data fidelity operator, based on the Gamma likelihood model for speckle noise, is incorporated to ensure physics-based consistency in SAR image despeckling.
3) A plug-and-play based denoising prior is incorporated into the CE framework, allowing for the flexible utilization of advanced denoisers.
4) Experimental results on representative SAR images demonstrate the effectiveness of the proposed framework in speckle reduction and structural preservation, when compared to several recent despeckling techniques.

The remainder of the paper is organized as follows. Section II presents the problem formulation and the SAR observation model. Section III describes the proposed consensus equilibrium-based despeckling framework. Section IV presents the results and performance evaluation. Finally, Section V concludes the paper and outlines future research directions.

II. Problem Formulation

SAR images are inherently affected by speckle noise due to the coherent nature of microwave imaging. The observed SAR intensity image can be modeled using a multiplicative noise model. Let $y \in \mathbb{R}^{M\times N}$ denote the observed speckled SAR image and $x \in \mathbb{R}^{M\times N}$ represent the underlying reflectivity image. The observation model is given by

$$y = x \odot n, \tag{1}$$

where n denotes the speckle noise and $\odot$ represents element-wise multiplication. For an L-look SAR image, the speckle component is commonly modeled using a Gamma distribution,

$$n \sim \text{Gamma}(L, L), \tag{2}$$

where L is number of looks. Under this model, the probability density of the observation y given the reflectivity x is as follows:

$$p(y|x) = \frac{L^L}{\Gamma(L)} \frac{y^{L-1}}{x^L} \exp\left(-\frac{Ly}{x}\right). \tag{3}$$

The negative logarithm of the likelihood leads to the following data term:

$$\mathcal{D}(x) = L \sum_i \left(\frac{y_i}{x_i} + \log x_i\right). \tag{4}$$

The SAR despeckling problem can therefore be formulated as an inverse problem in which the goal is to estimate the latent reflectivity image x from the noisy observation y. Traditional approaches solve this problem by minimizing the following:

$$\min_x \ \mathcal{D}(x) + \lambda R(x), \tag{5}$$

where $R(x)$ is a regularization term that encodes prior information about the underlying image structure, and λ is a balancing parameter. However, such formulations tightly couple the data fidelity and prior terms within a single objective, limiting flexibility in incorporating heterogeneous priors or advanced denoising operators. To address this limitation, we adopt a CE formulation in which the restoration problem is interpreted as an equilibrium between complementary operators.

III. Proposed Consensus Equilibrium Framework

In this section, we present the proposed CE framework for SAR image despeckling. Instead of minimizing a single composite objective function, the CE formulation interprets restoration as an equilibrium among complementary operators. This perspective enables flexible integration of a physics-consistent data fidelity operator with learned denoising priors.

A. Operator Formulation

Let $F_1(\cdot)$ denote the data fidelity operator derived from the SAR observation model, and $F_2(\cdot)$ represent a denoising prior operator. The data fidelity operator enforces consistency with the multiplicative SAR observation model, while the denoising operator suppresses speckle noise by exploiting structural

properties of SAR images. The data fidelity operator is defined as

$$F_1(v) = \arg\min_x \Big\{ L \sum_i \Big(\frac{y_i}{x_i} + \log x_i \Big) + \frac{\rho}{2} \|x - v\|_2^2 \Big\}. \tag{6}$$

where the penalty parameter ρ controls the strength of the proximal term. The data-fidelity operator $F_1(\cdot)$ is separable across pixels. For each pixel, Eq. (6) can be solved as

$$\phi_i(x_i) = L \left(\frac{y_i}{x_i} + \log x_i \right) + \frac{\rho}{2}(x_i - v_i)^2, \quad x_i > 0. \tag{7}$$

Though the presence of the logarithmic term makes (7) non-convex, it can be solved using Newton iterations under the positivity constraint. The update at iteration t is given by

$$x_i^{(t+1)} = x_i^{(t)} - \eta \frac{\phi_i'(x_i^{(t)})}{\phi_i''(x_i^{(t)})}, \quad 0 < \eta \leq 1, \tag{8}$$

where $\phi_i'(x_i) = -\frac{Ly_i}{x_i^2} + \frac{L}{x_i} + \rho(x_i - v_i)$, and $\phi_i''(x_i) = \frac{2Ly_i}{x_i^3} - \frac{L}{x_i^2} + \rho$. After each update, the estimate is projected onto the feasible set to maintain positivity, i.e., $x_i^{(t+1)} = \max(x_i^{(t+1)}, \epsilon)$, for a small $\epsilon > 0$. In practice, only a few Newton iterations are sufficient to obtain an accurate evaluation of $F_1(v)$. The denoising operator is implemented using a residual-learning prior and is defined as

$$F_2(v) = v - D(v), \tag{9}$$

where $D(\cdot)$ denotes a residual denoiser that estimates the speckle component in the input image. The restored image is obtained by subtracting the predicted residual from the current estimate. The residual form is similar to the DnCNN model and allows for the efficient removal of speckle noise in SAR images while preserving structural details.

B. Consensus Equilibrium Formulation

The CE framework seeks a fixed point where the outputs of complementary operators reach consensus. Specifically, the equilibrium solution satisfies

$$F_1(x + u_1) = x \quad \text{and} \quad F_2(x + u_2) = x, \tag{10}$$

subject to the consistency condition $u_1 + u_2 = 0$. This formulation balances the effects of the physics-consistent SAR observation model and the learned denoising prior, allowing the restoration process to reach a stable equilibrium that simultaneously enforces data fidelity and structural regularization.

C. Iterative Solution

The equilibrium solution can be obtained using an iterative fixed-point scheme. At iteration k, each operator processes a shifted estimate of the current solution. Specifically, the data-consistency and denoising operators are applied as

$$z_1^{k+1} = F_1(x^k + u_1^k) \quad \text{and} \quad z_2^{k+1} = F_2(x^k + u_2^k), \tag{11}$$

where z_1^{k+1} enforces consistency with the SAR observation model and z_2^{k+1} performs speckle suppression using the denoising prior. A consensus estimate is then obtained by averaging the operator outputs,

$$x^{k+1} = \frac{1}{2}(z_1^{k+1} + z_2^{k+1}), \tag{12}$$

which balances both the data fidelity and denoising operators. The auxiliary variables are subsequently updated as

$$u_1^{k+1} = u_1^k + z_1^{k+1} - x^{k+1}, \tag{13}$$

$$u_2^{k+1} = u_2^k + z_2^{k+1} - x^{k+1}, \tag{14}$$

to enforce consistency between the operator outputs and the consensus estimate. The overall residual-aware consensus equilibrium SAR despeckling procedure is summarized in Algorithm 1.

Algorithm 1 Residual-Aware CE for SAR Despeckling

Require: Speckled image y, penalty ρ, max. iterations K
Ensure: Despeckled image x

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Initialize x^0 = y, u_1^0 = 0, u_2^0 = 0
for k = 0, 1, ..., K − 1 do
    z_1^{k+1} = F_1(x^k + u_1^k)            ▷ Data fidelity operator
    z_2^{k+1} = F_2(x^k + u_2^k)            ▷ Residual denoising operator
    x^{k+1} = 1/2 (z_1^{k+1} + z_2^{k+1})   ▷ Consensus update
    u_1^{k+1} = u_1^k + z_1^{k+1} − x^{k+1}
    u_2^{k+1} = u_2^k + z_2^{k+1} − x^{k+1}
    if Stopping criterion satisfied then
        break
    end if
end for
    return x^{k+1}
```

D. Stopping Criterion

The iterative process is terminated when the relative change between two consecutive estimates falls below a predefined tolerance ϵ. Specifically, the stopping condition is defined as

$$\frac{\|x^{k+1} - x^k\|_2}{\|x^k\|_2} < \epsilon, \tag{15}$$

In our experiments, ϵ is set to 10^{-4}. The algorithm is also stopped if the maximum number of iterations K is reached.

IV. Experimental Results

This section evaluates the performance of the proposed physics-guided consensus equilibrium (CE) framework for SAR image despeckling. Experiments are conducted under different speckle conditions, and the results are compared with representative despeckling methods from different methodological categories.

A. Experimental Setup and SAR Data

The proposed method is evaluated on benchmark images commonly used in SAR despeckling studies. To model the degradation caused by speckle, multiplicative noise with a Gamma distribution is used to degrade clean reference images. Two different speckle conditions, corresponding to $L = 1$ and

$L = 5$ looks, are considered. The case of $L = 1$ represents a high level of speckle degradation, as typically found in single-look SAR images, while the case of $L = 5$ represents a moderate speckle condition. All experiments are implemented in MATLAB R2021b. The penalty parameter ρ is empirically selected based on the noise level, and the maximum number of consensus equilibrium iterations is fixed to K. For the data fidelity operator $F_1(\cdot)$, a few safeguarded Newton iterations are employed to efficiently compute the proximal update under the positivity constraint.

Fig. 1(a) presents a 392×392 MiniSAR image of a power substation, while Fig. 1(b) shows a 600×600 Ka-band SAR image at the Jacksonville Naval Air Station. These are collected from [14]. Similarly, the practical SAR images shown in Figs. 1(c) and (d) are Sentinel-1B IW complex Level-1 intensity images of size 792×792, obtained from [15]. The regions highlighted by yellow boxes in Figs. 1(b) and (c) are used to illustrate the effects of noise and despeckling for both simulated and practical SAR images.

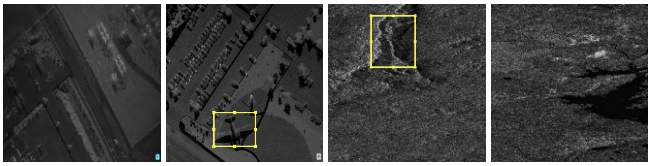


Fig. 1: SAR data used: (a) SSAR1 (MiniSAR), (b) SSAR2 (Ka-band), (c) PSAR1 and (d) PSAR2 (Sentinel-1B).

B. Comparison Methods and Evaluation Metrics

The proposed method is compared with transform-domain approaches such as NL-SAR [2] and MuLoG [3], the self-supervised deep learning method Speckle2Void [6], and the plug-and-play (PnP) restoration framework [10]. Reference-based metrics, including peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), and mean absolute error (MAE), evaluate the fidelity of the restored image with respect to the ground-truth image for simulated data [16]. For practical SAR images, for which there are no available ground truth data, no-reference measures such as equivalent number of looks (ENL), edge preservation index (EPI), and speckle suppression index (SSI) are employed to evaluate speckle reduction and structural preservation in homogeneous and textured areas. For simulated SAR images, the theoretical ENL for these images corresponds to the number of looks L. After despeckling, ENL increases due to the reduction in variance. However, very high ENL values indicate oversmoothing. Hence, ENL and structural preservation measures EPI and SSI are employed.

C. Results and Discussion

Table I depicts the quantitative evaluation of the proposed approach with respect to the competing methods for both simulated and real SAR image datasets. For the simulated image datasets, the proposed CE approach yields the best PSNR and SSIM values along with the least MAE for all test cases ($L = 1$ and $L = 5$). For example, for the SSAR1 image with $L = 5$, the proposed approach yields the best PSNR and SSIM values of 30.57 and 0.902, respectively, and the least MAE compared to all the competing approaches.

For the practical SAR image datasets for which the reference image is not available, the proposed approach yields the best values for the ENL (22.4 and 19.6 for PSAR1 and PSAR2 images, respectively) along with the best EPI and SSI values. The number of looks in these images is not explicitly known and is estimated from homogeneous regions. A uniform patch is selected, and the look number is estimated as $L = \mu^2/\sigma^2$, where μ and σ^2 are the sample mean and variance of the region, respectively. The estimated values of L for the considered images lie in the range of approximately 18–22, indicating effective speckle reduction after processing. This demonstrates that the proposed framework effectively suppresses speckle noise without compromising structural and edge information. In contrast, classical methods such as NL-SAR and MuLoG achieve lower ENL or structural preserva-

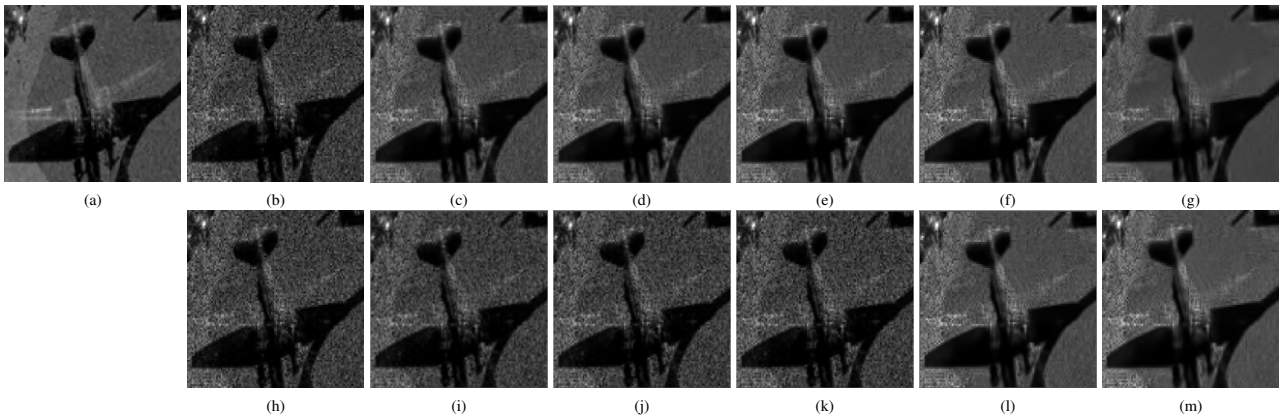
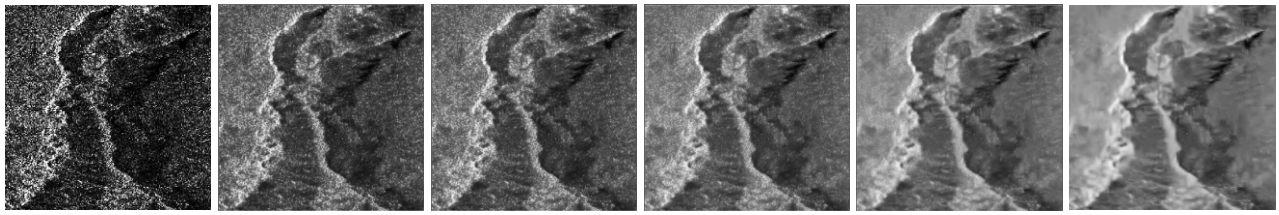


Fig. 2: Visual comparison of despeckling results on simulated SAR images: (a) clean reference image, (b) speckled image, (c) NL-SAR [2], (d) MuLoG [3], (e) Speckle2Void [6], (f) PnP [10], and (g) Proposed method for $L = 5$. (h)–(m) Corresponding results for $L = 1$ in the same order.



(a) (b) (c) (d) (e) (f)

Fig. 3: Visual comparison of despeckling results on practical SAR images: (a) noisy SAR image, (b) NL-SAR [2], (c) MuLoG [3], (d) Speckle2Void [6], (e) PnP [10], and (f) Proposed method.

TABLE I: Quantitative comparison of SAR despeckling performance using reference-based and no-reference metrics.

Methods	**Simulated SAR Images**												**Practical SAR Images**					
	SSAR1						**SSAR2**						**PSAR1**			**PSAR2**		
	PSNR (dB) ↑	**SSIM** ↑	**MAE** ↓	**PSNR (dB)** ↑	**SSIM** ↑	**MAE** ↓	**PSNR (dB)** ↑	**SSIM** ↑	**MAE** ↓	**PSNR (dB)** ↑	**SSIM** ↑	**MAE** ↓	**ENL** ↑	**EPI** ↑	**SSI** ↑	**ENL** ↑	**EPI** ↑	**SSI** ↑
	$L=1$			$L=5$			$L=1$			$L=5$			Estimated $L=\mu^2/\sigma^2$			Estimated $L=\mu^2/\sigma^2$		
NL-SAR [2]	24.10	0.842	0.058	29.20	0.884	0.026	23.85	0.838	0.060	28.10	0.872	0.030	18.5	0.71	0.79	16.2	0.69	0.76
MuLoG [3]	24.55	0.851	0.054	29.85	0.892	0.024	24.20	0.846	0.056	28.75	0.880	0.028	20.1	0.74	0.81	17.8	0.72	0.78
Speckle2Void [6]	24.80	0.860	0.052	30.05	0.895	0.023	24.35	0.855	0.054	28.95	0.885	0.027	17.2	0.76	0.83	15.8	0.74	0.80
PnP [10]	24.95	0.865	0.049	30.30	0.899	0.022	24.60	0.860	0.051	29.00	0.890	0.026	21.0	0.77	0.85	18.5	0.75	0.82
Proposed CE	**25.07**	**0.868**	**0.046**	**30.57**	**0.902**	**0.021**	**24.73**	**0.864**	**0.048**	**29.09**	**0.893**	**0.026**	**22.4**	**0.79**	**0.88**	**19.6**	**0.77**	**0.85**

tion, while learning-based approaches such as Speckle2Void exhibit comparatively lower noise suppression.

Fig. 2 shows the qualitative comparison results for both simulated and real SAR images. For simulated cases, transform-domain methods tend to produce residual speckle or over-smoothed regions, while deep learning-based methods may introduce texture inconsistencies. The PnP method also improves the balance but with a slight loss in fine structures. On the other hand, the proposed CE framework provides clean and homogeneous regions while preserving edges and fine details, especially for high-contrast boundaries and structural regions. Similar results are obtained for practical SAR images, as demonstrated in Fig. 3. The proposed method provides a better trade-off between speckle reduction and structure preservation.

V. Conclusion and Future Work

In this paper, a physics-guided consensus equilibrium (CE) framework has been proposed for SAR image despeckling in the multiplicative domain. The proposed method formulates despeckling as an equilibrium among complementary operators, integrating a Gamma-likelihood-based data fidelity term with a residual denoising prior. This enables a flexible combination of model-based and learning-based priors. Experimental results on both simulated and practical SAR images show that the proposed method achieves improved speckle suppression while preserving structural details. The framework consistently attains higher PSNR and SSIM with lower MAE, along with improved ENL, EPI, and SSI compared to classical, deep learning-based, and hybrid approaches. Future work will focus on extending the framework to multi-channel and polarimetric SAR data, incorporating adaptive priors, and exploring more advanced learned denoisers within the CE formulation.

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