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ATTENTION-DRIVEN DEEP IMAGE PRIOR FOR RADAR RESTORATION WITH KNOWN PSF

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ABSTRACT

Radar image restoration is often challenged by system blur and speckle noise, which degrade target visibility and structural fidelity. In this work, we evaluate three restoration approaches—Richardson–Lucy deconvolution with total variation regularization (RL+TV), Deep Image Prior (DIP), and a new attention-enhanced framework combining DIP with the Convolutional Block Attention Module (DIP+CBAM). A point-spread function (PSF) was extracted from a measured corner reflector and used to simulate realistic degraded radar images. Experimental results show that RL+TV provides limited recovery of fine details, achieving a PSNR of 14.66 dB and SSIM of 0.4969. DIP substantially improves reconstruction quality (PSNR 19.39 dB, SSIM 0.5267), benefiting from the implicit prior of untrained networks. The proposed DIP+CBAM method further enhances performance, reaching the highest PSNR (19.54 dB) and SSIM (0.5361). These findings demonstrate that integrating attention mechanisms into DIP offers a more effective prior for radar image restoration and leads to clearer, more structurally accurate reconstructions.

KEYWORDS

Deep Image Prior, Attention, Point Spread Function

1. INTRODUCTION

Radar imaging plays a critical role in remote sensing, surveillance, and navigation systems due to its ability to operate under diverse weather and lighting conditions. However, radar images often suffer from degradation caused by the system's point spread function (PSF), speckle, and measurement noise, leading to blurred and low-contrast observations that limit downstream analysis and interpretation **[1–4]**. Accurate restoration of radar images is therefore essential for applications ranging from target detection to scene understanding **[5–7]**.

Traditional image restoration techniques for radar signals are predominantly based on optimization-driven deconvolution methods. Methods such as Wiener filtering, Richardson–Lucy deconvolution, and regularized inverse problems rely on strong priors or multiple measurements to recover the underlying signal **[8–11]**. While effective in controlled settings, these approaches are often impractical in radar applications due to the difficulty in obtaining large datasets, the variability of target scenes, and the sensitivity to noise. Moreover, handcrafted priors may fail to capture complex radar-specific features, such as speckle patterns and structured clutter, limiting restoration quality **[12–14]**.

In recent years, deep learning has demonstrated remarkable success in image restoration tasks, including denoising, super-resolution, and deblurring **[15–17]**. However, most supervised deep learning approaches require extensive paired datasets for training, which are rarely available in

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radar contexts. To overcome this limitation, Ulyanov et al. **[18]** proposed the Deep Image Prior (DIP) framework, which leverages the intrinsic inductive bias of convolutional networks to restore images from a single degraded observation without external training data. DIP and its follow-up variants **[19–21]** have shown impressive results in natural image denoising and inpainting, suggesting potential applicability to radar image restoration. Several recent works have also explored DIP-based despeckling and inverse problem solutions in SAR domains **[22]**.

Despite its promise, the baseline DIP framework may produce overly smooth reconstructions and is susceptible to noise amplification, especially in high-noise environments **[19–21]**. Attention mechanisms, such as the Convolutional Block Attention Module (CBAM) **[23]**, have been shown to enhance deep networks by selectively focusing on informative spatial regions and feature channels. Advanced attention models, including non-local and dual-attention frameworks **[24–26]**, demonstrate improved structure recovery in restoration tasks. Integrating attention into DIP could therefore improve the recovery of salient structures while suppressing noise artifacts. Furthermore, regularization strategies such as Total Variation (TV) and entropy-based penalties can stabilize optimization and prevent overfitting to noise, improving perceptual quality **[27–28]**.

In this work, we investigate attention-augmented Deep Image Prior for single-image radar restoration with a known PSF. We extend the DIP framework with spatial and channel attention modules and introduce additional regularization terms to enhance stability and structural fidelity. Our experimental results on radar imagery demonstrate that the proposed approach improves perceptual quality, particularly edge sharpness and structural similarity, while remaining a training-free, lightweight method suitable for resource-constrained radar platforms

2. METHODS

1. Richardson–Lucy (RL) deconvolution

RL is an iterative technique used to sharpen images that have been blurred by the radar system’s point spread function (PSF) or motion effects. The algorithm starts with an initial guess of the true image and repeatedly refines it by comparing the convolution of the guess with the PSF to the observed radar image. It is particularly effective in handling noise that follows a Poisson-like distribution, making it useful for improving resolution and revealing fine details in radar imaging.

For a blurred radar image I_{obs} using the system’s point spread function (PSF) P. It updates an estimate of the true image I_k at iteration k as

$$I_{k+1} = I_k(x,y) \cdot \left[\frac{I_{obs}(x,y)}{(I_k * P)(x,y)} * P^{flip}(x,y) \right] \tag{1}$$

where * denotes convolution, and P^{flip} is the PSF flipped in both axes.

2. Deep Image Prior

The core concept DIP is that convolutional architectures naturally favor the generation of smooth, structured, and spatially coherent patterns (such as edges, shapes, and textures), while requiring more iterations to reproduce high-frequency noise. This implicit bias allows the network to serve as an effective prior in inverse problems, guiding the reconstruction toward natural image statistics even without external training.

Given a degraded image (y) and a forward degradation operator (H) (e.g., convolution with a known PSF), DIP can be formulated as;

$$\theta^* = \arg\min_{\theta} \left\| Hf_\theta(z) - y \right\|_2^2 \quad (2)$$

where $f_\theta()$ *is* an untrained CNN with parameters θ ,z is a fixed random noise vector or low-dimensional noise image. H is models the blurring operator or radar system PSF. The reconstructed image is obtained as:

$$y^{est} = f_{\theta^*}(z) \quad (3)$$

The general objective with entropy-based regularization become

$$\theta^* = \arg\min_{\theta} \left\| Hf_\theta(z) - y \right\|_2^2 + \lambda R(f_\theta(z)) \quad (4)$$

3. Attention-Augmented Deep Image Prior (DIP+CBAM)

To enhance the baseline Deep Image Prior (DIP) framework for radar image restoration, we incorporate both channel and spatial attention mechanisms into the untrained CNN architecture. The resulting method, referred to as DIP+CBAM, improves reconstruction quality by adaptively emphasizing informative features while suppressing irrelevant or noisy regions.

Channel Attention computes a per-channel weight to emphasize important feature maps. For an intermediate feature map $F \in \Re^{C\times H\times W}$ the channel attention $M_c(F) \in \Re^{C\times 1\times 1}$ is computed as:

$$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F)) \quad (5)$$

where AvgPool and MaxPool compute global average and max along spatial dimensions. MLP is a shared multi-layer perceptron and σ is the sigmoid activation.

Spatial Attention highlights salient spatial regions within each feature map. For feature map F' , the spatial attention

$$M_s(F') = \sigma(f^{7\div 7}([AvgPool_{chan}(F'); MaxPool_{chsn}(F'')])) \quad (6)$$

Where $AvgPool_{chan}$ and $MaxPool_{chan}$_are pool along the channel dimension, $f^{7\times 7}$ is a 7×7 convolution.

The resulting spatial attention map is multiplied element-wise:

$$F'' = M_s(F') \circ F' . \quad (7)$$

CBAM modules are inserted after each convolutional block in both encoder and decoder paths as shown in Figure 1.

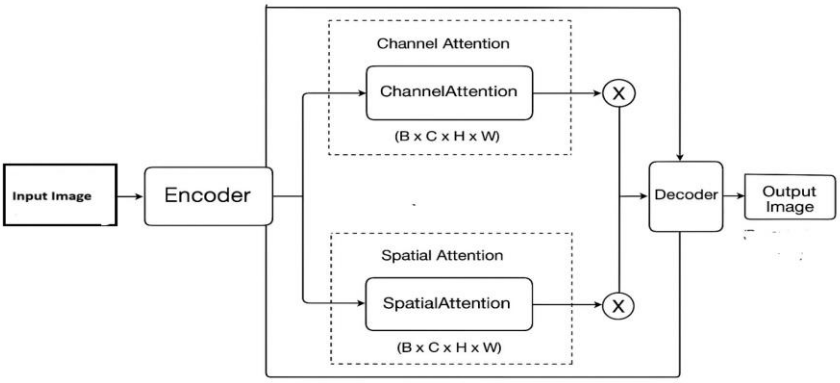


Figure 1, Proposed DIP + CBAM method

3. EXPERIMENTS AND RESULTS

This section describes the experimental setup used to evaluate three restoration methods—Richardson–Lucy (RL), Deep Image Prior (DIP), and the proposed DIP+CBAM—on radar images blurred by a point-target point spread function (PSF).The PSF is obtained from a calibrated measurement using a metallic trihedral corner reflector placed in the radar scene. The reflector serves as an ideal point scatterer with high radar cross section. Figure 2 shows the PSF.

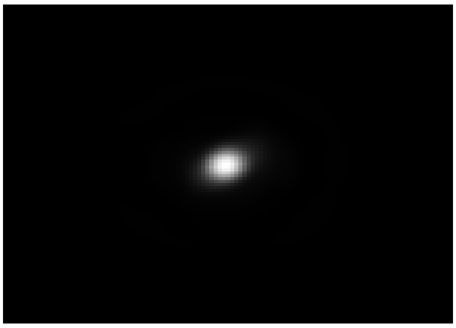


Figure 2 The PSF of the radar system

Figure 3 (a), (b) , (c) and (d) show the original image, image restored by the RL algorithm, image restored by the DIP algorithm and the image restored by our proposed algorithm respectively.

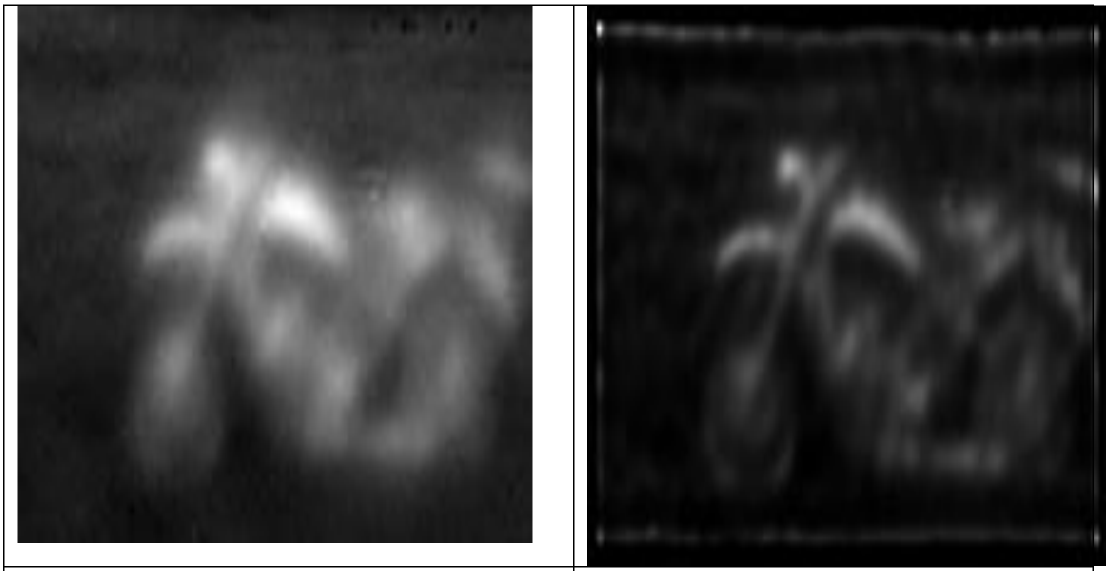
We use the Peak Signal-to-Noise Ratio (PSNR) [8] and the Structural Similarity Index (SSIM) [30] to evaluate the quality of the restored images. PSNR is defined using the mean squared error (MSE) between the two images, with higher PSNR values indicating better reconstruction quality. Unlike PSNR, SSIM models human visual perception and provides a more reliable indication of how well structural features (edges, textures, shapes) are preserved in the restored image. SSIM values range from 0 to 1, with higher values indicating greater structural fidelity.

The quantitative results in Table 1 show the performance among the three restoration methods.

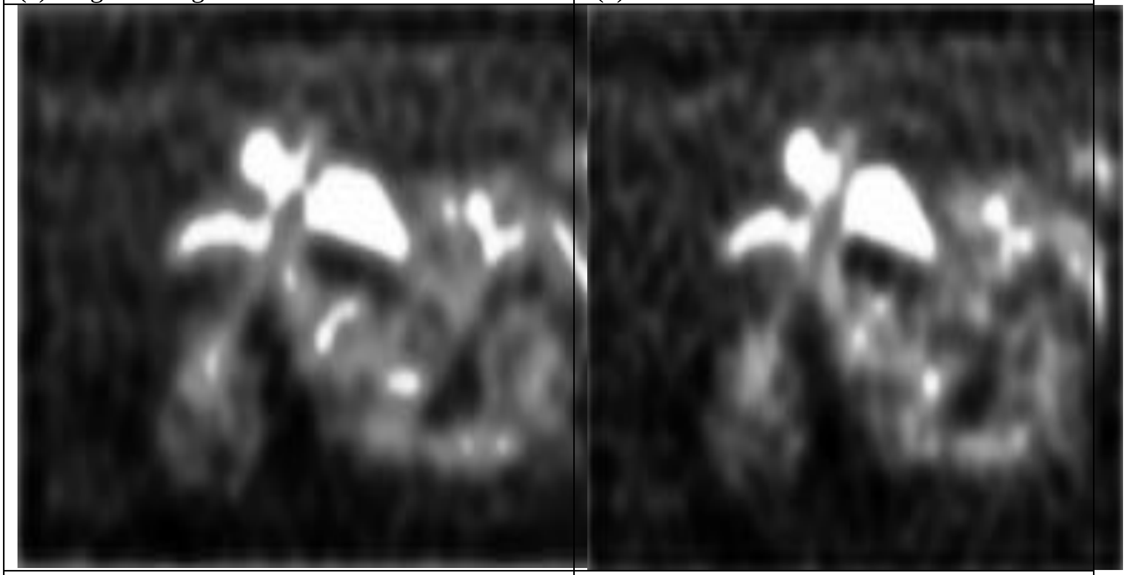
Table 1. Quantitative Comparison of Image Restoration Methods

Method	PSNR (dB)	SSIM
RL	14.66	0.4969
DIP	19.39	0.5267
DIP + CBAM	19.54	0.5361

The results of the RL method demonstrates the limitations of classical deconvolution for complex radar blur patterns. DIP shows a significant improvement over RL method DIP offers a strong, architecture-driven prior that restores global structures better than classical methods. However, DIP may partially overfit to noise at later iterations, limiting the achievable SSIM. The proposed method achieves the best overall performance: with highest SSIM(0.5361) and highest PSNR(19.54 dB) It implies that CBAM strengthens DIP by guiding the network to focus on physically meaningful radar structures, yielding better detail preservation and structural similarity.



(a) Original Image | (b) R L restoration



(c) DIP restoration | (d) Proposed DIP +CBAM restoration

Figure 3 (a) Original image from radar system (b) Image restored from the RL algorithm (c) Image restored by the DIP algortihm (d) Image restored by the our proposed DIP+CBAM

4. CONCLUSIONS

This study compared RL+TV, DIP, and the proposed DIP+CBAM method for radar image restoration using a measured corner-reflector PSF. RL+TV produced the weakest reconstruction, while DIP provided a substantial improvement by exploiting the implicit priors of an untrained network. The proposed DIP+CBAM achieved the best overall performance, with the highest PSNR and SSIM, showing that attention mechanisms help the network focus on salient radar features and suppress noise. These results demonstrate that combining DIP with CBAM offers an effective and robust solution for radar image restoration.

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