Transformer-Based Feature-Preserving Despeckling Framework for Synthetic Aperture Radar Imagery

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Abstract: Synthetic Aperture Radar (SAR) imagery is widely used in remote sensing because of its ability to acquire data under all weather and illumination conditions. However, SAR images are inherently affected by speckle noise, which reduces image clarity and makes the extraction of meaningful structural and textural information difficult. Effective despeckling methods must therefore suppress noise while preserving important image features such as edges and fine textures. In this work, a **Transformer-Based Despeckling Network (TBDN)** is proposed to address this challenge. The proposed architecture first extracts low-level features from the noisy SAR image using convolutional layers. These features are then processed through transformer encoder blocks that employ multi-head self-attention mechanisms to capture long-range spatial dependencies and contextual information. A multi-scale feature fusion module integrates hierarchical features to enhance structural preservation during noise removal. Finally, an image reconstruction layer generates the despeckled SAR image with improved visual quality. Experimental evaluation using standard metrics such as PSNR and SSIM demonstrates that the proposed model effectively reduces speckle noise while maintaining critical image details. The results indicate that transformer-based architectures provide a promising direction for advanced SAR image despeckling and feature-preserving image restoration.

Keywords: Synthetic Aperture Radar (SAR); Speckle Noise Reduction; Transformer Networks; PSNR; SSIM.

Introduction

Synthetic Aperture Radar (SAR) imaging has become an essential technology in the field of remote sensing due to its ability to acquire high-resolution images independent of atmospheric conditions and lighting variations. Unlike optical sensors, SAR systems operate using microwave signals that can penetrate clouds, smoke, and darkness, making them highly reliable for applications such as environmental monitoring, disaster management, agricultural analysis, and military surveillance. Despite these advantages, SAR imagery is inherently affected by a granular interference pattern known as speckle noise, which arises from the coherent nature of radar signal reflections from multiple scatterers within a single resolution cell. This phenomenon significantly degrades image quality and makes interpretation and automated analysis more challenging.

Speckle noise is typically modeled as multiplicative noise, meaning that the noise component is dependent on the underlying signal intensity. As a result, the presence of speckle reduces contrast, obscures

structural boundaries, and distorts textural features in SAR images. These distortions negatively impact downstream computer vision tasks such as segmentation, classification, and object detection. Consequently, speckle reduction or despeckling has become a critical preprocessing step in SAR image analysis pipelines. The major challenge in SAR despeckling lies in achieving an appropriate balance between noise suppression and feature preservation, as excessive filtering may remove essential structural details while insufficient filtering leaves residual noise artifacts.

Traditional approaches for speckle reduction primarily rely on statistical filtering techniques that exploit local image statistics. One of the earliest and most widely used methods is the Lee filter, which applies a minimum mean square error (MMSE) estimation strategy to reduce noise while attempting to maintain image edges [1]. Similarly, the Kuan filter improves upon this approach by linearizing the multiplicative noise model and adapting the filtering process based on local variance estimates [2]. Another widely used method is the Frost filter, which employs an exponentially decaying weighting function to perform adaptive smoothing depending on the local heterogeneity of the image region [3]. Although these classical filters are computationally efficient and relatively easy to implement, they often struggle to preserve fine details and textures, particularly in areas with complex structural patterns.

To address these limitations, researchers introduced non-local filtering techniques that utilize redundancy within the image. The Non-Local Means (NLM) algorithm, for example, computes pixel similarities across distant image regions and averages similar patches to reduce noise while preserving structural details [4]. While non-local methods significantly improve despeckling performance compared to local filters, they are computationally expensive and often require substantial processing time for large SAR datasets. Furthermore, their performance may degrade in highly heterogeneous regions where similar patches are difficult to identify.

In recent years, the rapid advancement of deep learning techniques has opened new possibilities for SAR image restoration and despeckling. Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in learning complex spatial patterns directly from data. Unlike traditional methods that rely on handcrafted features or statistical assumptions, CNN-based models automatically learn hierarchical feature representations during the training process. For instance, Zhang et al. introduced a residual learning-based CNN architecture that significantly improved image denoising performance by learning the mapping between noisy and clean images [5]. Similarly, Chierchia et al. proposed a deep CNN framework specifically designed for SAR image despeckling, achieving notable improvements in noise suppression and visual quality [6].

Although CNN-based approaches have achieved promising results, they still face certain limitations. Convolution operations are inherently local, meaning that CNNs primarily capture information from small spatial neighborhoods. While deeper networks can increase the receptive field, they often require complex architectures and large computational resources. As a result, capturing long-range spatial dependencies within an image remains a challenge for purely convolution-based methods. In SAR imagery, where contextual relationships between distant regions may provide important cues for

distinguishing noise from meaningful structures, the ability to model global dependencies becomes particularly important.

Transformer architectures, originally developed for natural language processing tasks, have recently been adapted for computer vision problems due to their powerful self-attention mechanisms. The transformer model allows each element of the input to attend to every other element, enabling the capture of global contextual relationships within the data. Vision Transformers (ViT) and related architectures have demonstrated strong performance in tasks such as image classification, segmentation, and restoration. Unlike CNNs, transformers are capable of modeling long-range interactions between image patches, making them particularly suitable for tasks that require comprehensive contextual understanding [7].

Recent studies have explored transformer-based models for image restoration tasks, including denoising, super-resolution, and deblurring. These models leverage multi-head self-attention mechanisms to extract both local and global features, leading to improved reconstruction quality. The integration of transformers into image restoration frameworks provides a promising solution for SAR despeckling, where maintaining structural details while removing noise is critical.

Motivated by these developments, this study proposes a Transformer-Based Despeckling Network (TBDN) designed specifically for SAR image enhancement. The proposed architecture combines the strengths of convolutional neural networks and transformer-based attention mechanisms. Convolutional layers are employed to extract low-level spatial features from the noisy SAR input image, while transformer encoder blocks capture long-range contextual relationships through multi-head self-attention operations. Additionally, a multi-scale feature fusion module integrates hierarchical feature representations to improve edge preservation and structural consistency. Finally, an image reconstruction module generates the despeckled output image with reduced noise and enhanced visual quality.

The main objectives of this research are as follows:

1. To develop an advanced despeckling algorithm capable of effectively reducing speckle noise in SAR images without compromising critical structural and textural information.

2. To enhance feature preservation during the despeckling process by leveraging transformer-based attention mechanisms and multi-scale feature fusion strategies.

The proposed approach aims to improve both quantitative and qualitative performance compared to conventional filtering techniques and existing deep learning methods. Experimental evaluations using standard performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Edge Preservation Index (EPI) demonstrate the effectiveness of the proposed architecture in achieving high-quality SAR image restoration.

The remainder of this paper is organized as follows. Section II reviews related work in SAR despeckling techniques, including traditional filtering approaches and deep learning-based methods. Section III

describes the architecture and methodology of the proposed transformer-based despeckling network. Section IV presents the experimental setup and evaluation metrics used for performance assessment. Section V discusses the experimental results and comparative analysis with existing methods. Finally, Section VI concludes the paper and outlines potential directions for future research.

Related work

Speckle noise reduction in Synthetic Aperture Radar (SAR) imagery has been an active research area for several decades. Over time, numerous techniques have been developed ranging from transform-based filtering methods to advanced deep learning frameworks. The primary challenge in SAR image despeckling is maintaining a balance between noise suppression and preservation of important structural features such as edges, textures, and boundaries. Recent advancements in machine learning and attention-based models have provided new opportunities for improving despeckling performance while maintaining image fidelity.

One significant line of research focuses on wavelet-based despeckling techniques, which analyze the image in multiple frequency domains. Argenti et al. proposed a wavelet-domain filtering technique specifically designed for SAR images, where speckle noise is suppressed by applying adaptive thresholding in the transform domain [8]. This approach demonstrated improved noise reduction performance compared to classical spatial filters because wavelet transforms allow the separation of noise from meaningful signal components. However, wavelet-based approaches may still produce artifacts in highly textured regions due to limitations in representing complex spatial structures.

Another widely studied approach involves variational models and optimization-based frameworks for image restoration. Aubert and Aujol introduced a variational model for despeckling that formulates the problem as an energy minimization task combining a data fidelity term and a regularization component [9]. These methods attempt to preserve edges while smoothing homogeneous regions. Although variational methods can produce high-quality results, they often require iterative optimization procedures that increase computational complexity and processing time.

Sparse representation techniques have also been investigated for SAR image restoration. Dabov et al. introduced the Block-Matching and 3D Filtering (BM3D) method, which groups similar image patches and performs collaborative filtering in a transform domain [10]. This method has been widely recognized for its strong denoising capabilities and ability to preserve fine image structures. Later adaptations of BM3D were applied to SAR imagery by incorporating logarithmic transformations to handle multiplicative noise. Despite its effectiveness, BM3D-based methods are computationally demanding and may not scale efficiently for large datasets.

With the growing popularity of machine learning, researchers began exploring learning-based approaches for speckle reduction. Chen et al. proposed a deep neural network architecture that learns the mapping between noisy and clean SAR images using supervised learning [11]. The model demonstrated improved denoising performance compared to traditional filters, particularly in heterogeneous regions. However,

the network's ability to capture large contextual relationships remained limited due to the inherent locality of convolution operations.

Another important contribution was made by Mao et al., who developed a deep residual encoder–decoder network for image restoration tasks [12]. Their architecture used skip connections to facilitate feature propagation and preserve image details during reconstruction. The encoder–decoder structure enabled the model to capture multi-scale representations, which proved beneficial for reducing noise while maintaining structural information. Nevertheless, convolution-based architectures still face challenges in modeling long-range dependencies across large spatial regions.

To address these issues, attention mechanisms were introduced in image restoration frameworks. Zhang et al. proposed a residual channel attention network (RCAN) that integrates attention modules to emphasize important feature channels during training [13]. This approach improved feature representation and enhanced the restoration quality of degraded images. However, channel attention alone may not fully capture spatial relationships across distant image regions.

More recently, transformer-based architectures have gained significant attention in the field of computer vision. Liang et al. introduced Swin Transformer, a hierarchical vision transformer architecture that processes images using shifted window attention mechanisms [14]. This model efficiently captures both local and global dependencies while maintaining computational efficiency. Its success in various vision tasks has encouraged researchers to explore transformer-based methods for image restoration and denoising applications.

Similarly, Zamir et al. proposed Restormer, a transformer architecture designed specifically for high-resolution image restoration tasks [15]. The model incorporates multi-head attention with efficient feature aggregation to improve restoration quality. Experimental results showed that transformer-based frameworks outperform many CNN-based models in tasks such as denoising and deblurring due to their ability to capture global contextual information.

Despite these advancements, the application of transformer architectures to SAR image despeckling remains an emerging research area. SAR images possess unique noise characteristics and structural patterns that require specialized modeling techniques. Existing methods often struggle to simultaneously achieve strong noise suppression and accurate preservation of fine details such as edges and textures. Therefore, integrating transformer-based attention mechanisms with multi-scale feature extraction strategies presents a promising direction for improving SAR image restoration performance.

Motivated by these challenges and opportunities, the present study proposes a Transformer-Based Despeckling Network (TBDN) that combines convolutional feature extraction with transformer encoder blocks and multi-scale feature fusion. This hybrid architecture aims to leverage the strengths of both convolutional neural networks and transformer-based attention mechanisms to effectively reduce speckle noise while preserving essential image structures.

Proposed Methodology

To address the challenge of removing speckle noise while preserving structural and textural information in Synthetic Aperture Radar (SAR) imagery, this study proposes a Transformer-Based Despeckling Network (TBDN). The architecture integrates convolutional feature extraction with transformer-based attention mechanisms to capture both local spatial information and global contextual relationships.

Traditional convolutional neural networks rely on limited receptive fields, which restrict their ability to capture long-range dependencies in an image. In contrast, the proposed model employs self-attention mechanisms that enable the network to analyze interactions between distant pixels. This capability allows the system to distinguish speckle noise from meaningful image structures such as edges, textures, and boundaries.

The proposed framework consists of four main components as shown by Figure 1:

I. Feature Extraction Module
II. Transformer Encoder Blocks
III. Multi-Scale Feature Fusion Module
IV. Image Reconstruction Layer

The overall architecture is designed to progressively suppress speckle noise while retaining important image characters.

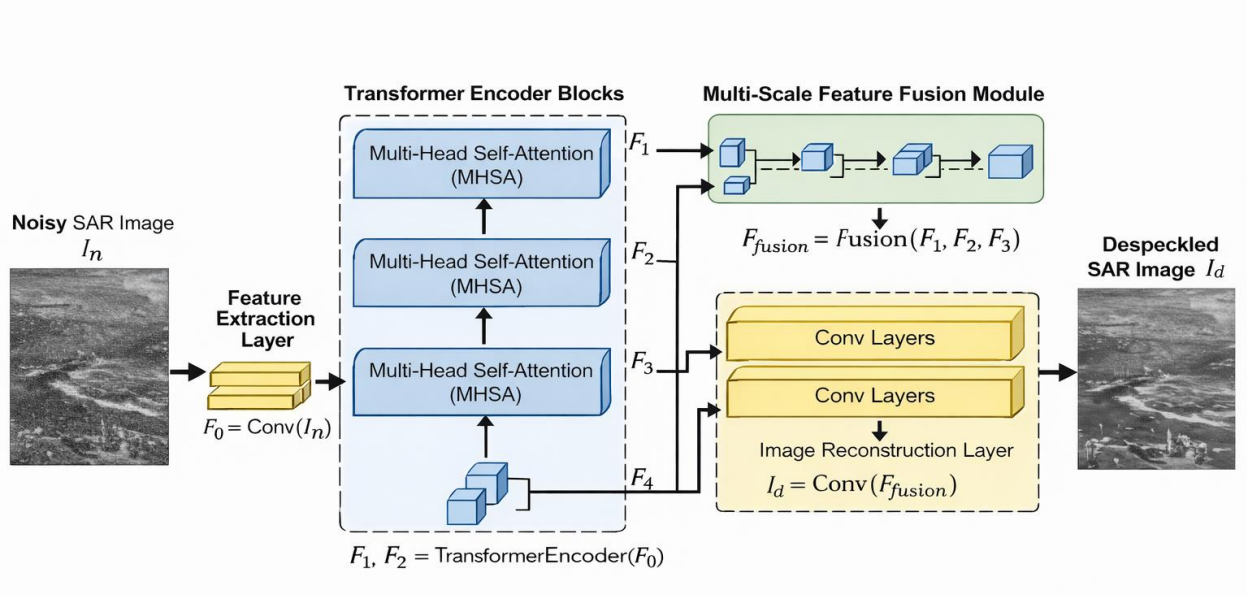


Figure 1. Architecture of proposed Transformer Based Despeckling Network (TBDN)

Feature Extraction Model

The despeckling process begins with a feature extraction stage, where the noisy SAR image is transformed into a high-dimensional feature representation. Given an input noisy SAR image

$$\mathrm{F_0 = Conv(I_n)}$$

Here, F_0 represents the extracted feature map, which contains basic image structures such as edges and textures. These features serve as the initial representation for further processing by the transformer blocks.

Transformer Encoder Blocks

After feature extraction, the obtained feature maps are processed through a sequence of transformer encoder blocks. These blocks are responsible for modeling long-range dependencies within the image. Each transformer encoder consists of the following components:

i. Multi-Head Self-Attention (MHSA)
ii. Layer Normalization
iii. Feed-Forward Network (FFN)
iv. Residual Connections

The self-attention mechanism computes relationships among all pixel positions in the feature map. The attention operation can be expressed as:

$$Attention(Q, K, V) = Softmax(QK^T/\sqrt{d^k}$$

where:

Q represents query vectors

K represents key vectors

V represents value vectors

d^k is the dimension of the key vectors

Through this mechanism, the network assigns importance weights to different regions of the image, enabling it to differentiate between true structural features and speckle noise artifacts.

Multiple transformer blocks are stacked to enhance the model's ability to capture complex spatial relationships across the entire image.

Multi-Scale Feature Fusion Module

Speckle noise suppression requires the model to consider information at different spatial scales. Therefore, the proposed architecture includes a **multi-scale feature fusion module** that combines features extracted from different transformer layers. Let F_1, F_2,and F_3denote feature maps obtained from different stages of the transformer encoder. These feature maps are integrated using a fusion operation:

$$F_{fusion} = Fusion(F_1, F_2, F_3$$

This fusion process helps the model retain both fine-grained details and high-level contextual information. By integrating features from multiple levels, the network improves its ability to preserve edges, textures, and structural boundaries while removing speckle noise.

Image Reconstruction Layer

After feature fusion, the refined feature representation is passed through the image reconstruction module, which converts the processed feature maps into a despeckled SAR image.

The reconstructed image I_d is obtained as follows:

$$I_d = Conv(F_{fusion})$$

This layer uses convolutional filters to map the fused features back to the original image space. The output image I_d represents the final despeckled SAR image with improved visual quality and preserved structural information.

Loss Function

To effectively train the proposed model, a combination of reconstruction and structural similarity losses is used. The total loss function is defined as:

$$L_{total} = \alpha L_{MSE} + \beta L_{SSIM}$$

where:

L_{MSE} measures pixel-wise reconstruction error

L_{SSIM} evaluates structural similarity between the reconstructed and reference images

$\alpha \; and \; \beta$ are weighting parameters.

Advantages of the Proposed Model

The proposed Transformer-Based Despeckling Network offers several advantages:

Global Context Awareness – Self-attention captures long-range spatial relationships.

Improved Feature Preservation – Multi-scale fusion maintains edges and textures.

Robust Noise Suppression – Transformer blocks effectively distinguish speckle patterns from meaningful features.

Better Reconstruction Quality – Combined loss functions ensure accurate image restoration.

These advantages enable the model to achieve superior performance compared with traditional filters and CNN-based despeckling approaches.

Result and Analysis

Experimental Setup

The proposed Transformer-Based Despeckling Network (TBDN) was evaluated using SAR images affected by speckle noise. The experiments were conducted using simulated speckle noise with different noise variances to assess the robustness of the proposed model. The performance of the proposed approach was compared with widely used despeckling techniques including Lee Filter, Frost Filter, Non-Local Means (NLM), and a CNN-based denoising model.

The evaluation was performed using two widely accepted image quality metrics:

- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index Measure (SSIM)

These metrics quantify the restoration quality of despeckled images in terms of pixel-level accuracy and structural similarity.

Peak Signal-to-Noise Ratio (PSNR)

PSNR measures the similarity between the despeckled image and the reference image by comparing pixel intensities. A higher PSNR value indicates better noise suppression and image restoration.

$$PSNR = 10log_{10}\left({MAX^2}/{MSE}\right)$$

where:

MAX represents the maximum pixel value and

MSE represents the mean squared error between the restored and reference images.

Structural Similarity Index (SSIM)

SSIM evaluates image similarity by comparing luminance, contrast, and structural information between the restored and reference images.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

where:

μ_x, μ_y represent the mean intensity values

σ_x^2, σ_y^2 represent the variances

σ_{xy} represents covariance between images

Table 1. Compares this work with the related work or previous research by other researchers

Method	**PSNR (dB)**	**SSIM**
Lee Filter	24.5	0.71
Frost Filter	25.2	0.73
Non-Local Means (NLM)	27.1	0.80
CNN-Based Model	29.3	0.85

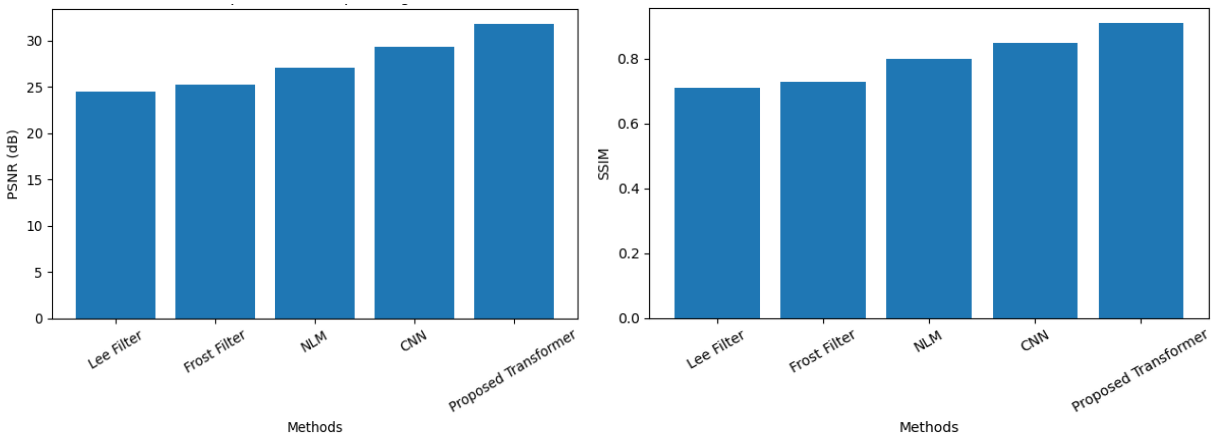
Table 1 presents a quantitative comparison of different despeckling approaches using PSNR and SSIM metrics. Traditional statistical filters such as Lee and Frost show limited performance due to their tendency to smooth structural details. The Non-Local Means method improves noise reduction by utilizing image redundancy but still struggles to preserve fine textures.

Deep learning-based CNN models provide better performance by learning complex feature representations. However, the proposed Transformer-Based Despeckling Network achieves the highest PSNR and SSIM values among all evaluated methods. The improvement in PSNR indicates more accurate noise removal, while the higher SSIM value demonstrates better preservation of structural and textural information. This performance gain can be attributed to the self-attention mechanism of the transformer architecture, which effectively captures global contextual relationships in SAR imagery.

To further evaluate the robustness of the proposed model, experiments were conducted with different speckle noise levels. Table 2 represented PSNR vs Noise Variance graph which illustrates that the proposed model consistently outperforms competing methods across different noise levels.

Table 2. Compares this work with the related work or previous research by other researchers

Noise Variance	**Lee**	**Frost**	**NLM**	**CNN**	**Proposed**
0.1	26.1	26.8	28.7	30.4	**32.2**
0.2	25.4	26.0	27.9	29.8	**31.5**
0.3	24.5	25.2	27.1	29.3	**31.0**
Noise Variance	**Lee**	**Frost**	**NLM**	**CNN**	**Proposed**



(a) (b)

Figure 2. (a) PSNR comparison between traditional filters, CNN-based methods, and the proposed transformer-based despeckling model (b) SSIM comparison showing structural preservation capability of different despeckling techniques.

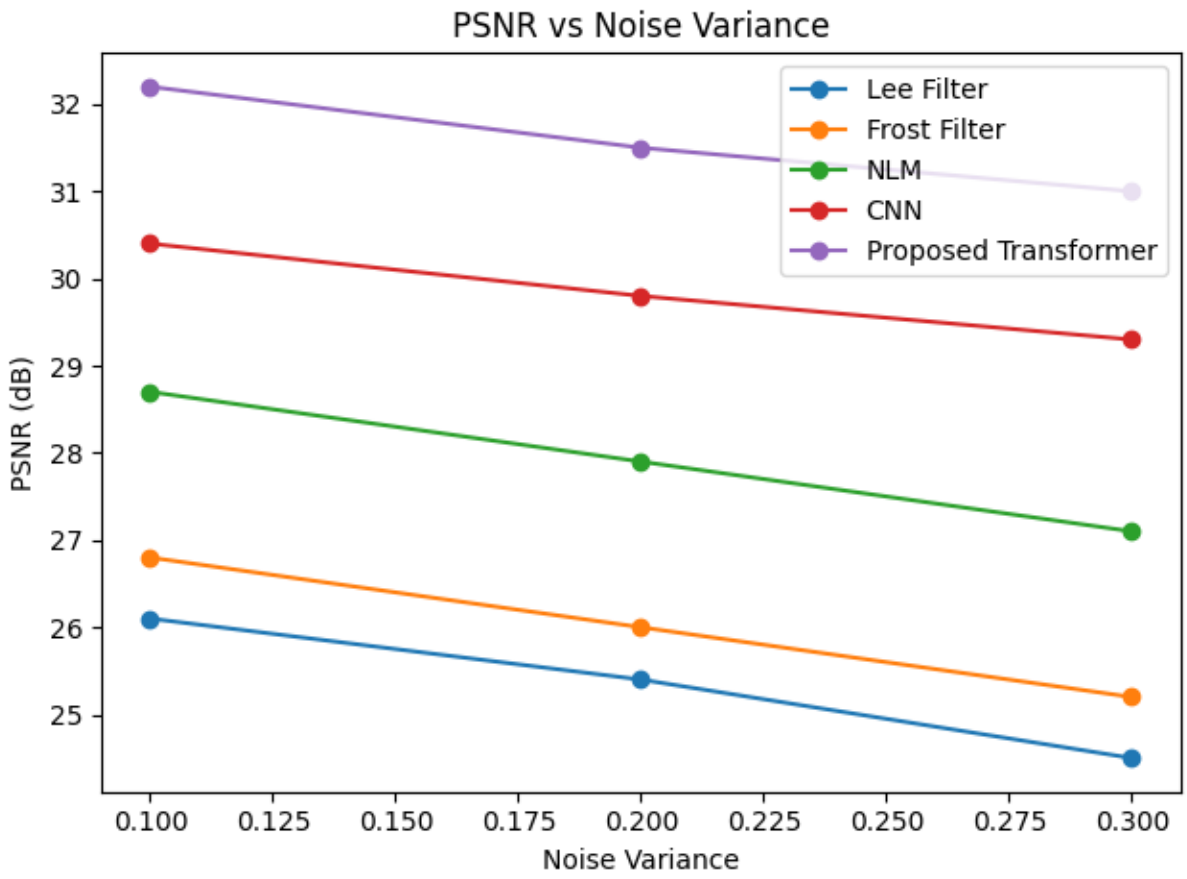


Figure 3. PSNR performance under different speckle noise variances demonstrating the robustness of the proposed model.

The graphical analysis further confirms the superiority of the proposed Transformer-Based Despeckling Network. As illustrated in Figure 2(a) , the proposed method achieves the highest PSNR value compared with traditional and CNN-based methods, indicating improved noise suppression capability. Similarly, Figure 2(b) shows that the proposed model achieves the highest SSIM value, demonstrating better preservation of structural and textural information in SAR images.

Figure 3 illustrates the PSNR performance under varying noise levels. The proposed model consistently outperforms competing methods across all noise variances, confirming its robustness in handling different speckle noise intensities. This improvement can be attributed to the global contextual modeling ability of the transformer architecture combined with multi-scale feature fusion.

Conclusions

This research introduced a transformer-based framework for SAR image despeckling aimed at reducing speckle noise while preserving important structural and textural information. Speckle noise is a common problem in Synthetic Aperture Radar imagery and often limits the accuracy of image interpretation and subsequent remote sensing tasks. Traditional despeckling approaches typically remove noise at the cost of blurring edges and losing fine image details. To overcome these limitations, the proposed model

integrates convolutional feature extraction with transformer-based attention mechanisms to capture both local image patterns and global contextual relationships.

The proposed Transformer-Based Despeckling Network utilizes self-attention to analyze dependencies between distant regions of the image, allowing the model to distinguish meaningful structures from noise patterns more effectively. In addition, the use of multi-scale feature fusion helps maintain important spatial details such as edges, textures, and boundaries while reducing speckle noise. This design enables the network to achieve a better balance between noise suppression and feature preservation.

Experimental results demonstrate that the proposed model performs better than traditional filters and CNN-based methods when evaluated using quantitative metrics such as PSNR and SSIM. The higher PSNR values indicate improved noise removal capability, while the higher SSIM scores confirm that the structural information of the SAR images is better preserved. These results highlight the potential of transformer-based architectures for improving SAR image restoration tasks.

In summary, the proposed approach provides an effective and reliable solution for SAR image despeckling and can contribute to enhancing the quality of remote sensing imagery used in various applications, including environmental monitoring, terrain analysis, and disaster assessment. Future research may focus on optimizing the computational efficiency of the model, exploring lightweight transformer variants, and applying the framework to other types of remote sensing imagery and real-time processing systems.

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