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Curvelet–Deep Learning Fusion Approach for Denoising and Enhancing Low-Light Remote Sensing Images

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***Abstract:** Low-light remote sensing images often suffer from severe noise and poor contrast due to insufficient illumination and atmospheric interference, making them challenging to analyze in practical applications. To address these issues, this paper proposes a novel Sparse Denoising Convolutional Neural Network (SD-CNN) that integrates the multi-scale, multi-directional properties of the Curvelet transform with the powerful feature-learning capacity of convolutional networks. Specifically, the Curvelet transform is employed as a sparse representation tool to decompose the input image into different scales and orientations, enabling effective separation of signal and noise components while preserving edge and curve structures. The CNN is then trained on this sparse representation to adaptively suppress noise, enhance contrast, and restore fine details that are often lost in traditional image-processing approaches.*

Extensive experiments conducted on simulated and real-world low-light remote sensing datasets demonstrate that the proposed SD-CNN significantly outperforms existing baseline methods, including traditional wavelet-thresholding techniques and pure CNN-based models. Quantitative metrics such as PSNR, SSIM, and visual assessments consistently show that SD-CNN yields higher reconstruction quality and better edge preservation, especially under strong Gaussian noise conditions ($\sigma = 25$). Moreover, this hybrid architecture reduces the number of model parameters by approximately 30% through sparse processing in the Curvelet domain, resulting in faster training and inference. Additionally, a dynamic batch normalization mechanism is introduced to enhance training stability and improve model convergence.

In summary, the proposed SD-CNN not only provides superior denoising and enhancement capabilities for low-light remote sensing images but also offers a parameter-efficient design that is well-suited for practical deployment. The findings highlight the potential of combining mathematical transforms with deep learning to tackle challenging image restoration problems in remote sensing and other computer vision tasks.

***Keywords:** Low-light remote sensing images; Curvelet-based sparse representation; Deep convolutional neural networks; Image denoising and enhancement; Multi-scale and multi-directional image analysis; Dynamic batch normalization; Noise-robust image restoration; Edge and structure preservation.*

I. Introduction

Remote sensing images are captured by satellites or airborne platforms using various types of sensors to collect data about the Earth's surface. These sensors operate across different spectral bands, ranging from visible light to radar waves, thereby enabling the acquisition of information that is often invisible to the human eye (USGS, 2023 [6]). Remote sensing plays a crucial role in applications such as environmental monitoring, urban planning, disaster management, and precision agriculture (Gorelick et al., 2017 [7]).

However, remote sensing images acquired under low-light conditions often suffer from significant degradation due to photon noise, motion-induced blur, and the loss of high-frequency structural details. Such degradation severely impacts the usability of these images in downstream tasks like object detection or land cover classification. Traditional denoising and enhancement methods, such as Wiener filtering and wavelet-based techniques, offer limited performance, particularly in preserving curved and edge structures in noisy environments (Candès et al., 2000 [1]; Liu et al., 2019 [4]). Wavelet transforms, while effective for certain types of signals, lack the directional sensitivity needed to accurately represent curved features, which are prevalent in remote sensing imagery of natural landscapes.

In recent years, deep convolutional neural networks have emerged as powerful tools for image denoising and enhancement. Models such as DnCNN (Zhang et al., 2020 [3]) and related residual-learning frameworks have demonstrated significant improvements over traditional approaches by learning complex noise patterns and restoring fine details. Nevertheless, these CNN-based methods often require substantial computational resources and memory, as they typically operate directly on spatial-domain representations of images. This makes their deployment on resource-constrained systems, such as onboard processing units in satellites or unmanned aerial vehicles, challenging.

To address these limitations, hybrid approaches that combine mathematical transforms with deep learning have gained increasing attention. For example, the Curvelet transform, known for its superior ability to represent multi-scale and multi-directional curved structures, provides a sparse representation that can effectively separate noise from meaningful image features (Candès et al., 2000 [1]). Integrating such sparse representations with deep learning architectures allows for reduced model complexity and accelerated processing while preserving critical structural information. Recent studies have explored similar ideas, such as wavelet-based deep learning models (Chen et al., 2019 [4]) and transformer-based frameworks (Chen et al., 2021 [5]), further highlighting the potential of combining domain-specific transforms with neural networks.

This paper proposes a novel Sparse Denoising Convolutional Neural Network framework that fuses Curvelet-based sparse representation with a convolutional network to jointly denoise and enhance low-light remote sensing images. The primary objectives are to achieve high denoising performance, preserve structural details, and reduce model complexity for practical deployment. Our contributions include the design of a hybrid architecture that reduces parameter count by approximately 30%, the introduction of a dynamic batch normalization strategy to stabilize training, and experimental validation demonstrating superior performance over state-of-the-art methods under severe noise conditions.

II. SD-CNN Model Integrating Curvelet Transform And Deep Learning

The proposed SD-CNN model integrates the Curvelet transform with a convolutional neural network to enable efficient and robust denoising and enhancement of low-light remote sensing images. Initially, the noisy input image is decomposed into six scales using the Curvelet transform, which offers a multi-scale and multi-directional representation well-suited for capturing smooth contours and edges. Among these scales, only the coefficients at the mid-to-high frequencies (scales 4–6) are retained to reduce the data dimensionality while preserving structurally significant details.

Next, a lightweight CNN comprising four convolutional layers with 32 to 64 filters per layer is constructed. Sparse skip connections are introduced across these layers to propagate important edge information directly and help the network focus on fine-grained features. The CNN is then trained to suppress noise in the retained Curvelet coefficients while preserving directional and scale-specific image details.

After refinement, the coefficients are transformed back into the spatial domain using the inverse Curvelet transform, producing a clean and enhanced output image that is visually sharper and more informative for further remote sensing tasks.

To enhance training stability under a range of noise intensities, we introduce a dynamic batch normalization mechanism with a noise-dependent momentum parameter. Specifically, the momentum γ_t is defined as a nonlinear function of the noise standard deviation σ:

$$\gamma_t = 0.9 + 0.1 \cdot \tanh\left(\frac{\sigma}{30}\right)$$

which provides smooth adaptation as σ\sigmaσ varies between 15 and 50. This dynamic adjustment improves convergence rates and yields better performance under varying noise levels.

Finally, the model is trained and validated on a synthetic dataset consisting of 10,000 low-light remote sensing images derived from the Landsat-8 archive. These images are degraded with additive Gaussian noise (σ ∈ [15, 50]), motion blur kernels ranging from 7 to 21 pixels, and low-illumination conditions with a simulated brightness reduction of 50%–80%. This diverse and challenging dataset enables a thorough evaluation of the SD-CNN model under realistic low-light and noisy conditions.

The proposed model utilizes the Curvelet transform in conjunction with SD-CNN - a deep convolutional neural network comprising 20 convolutional layers. The architecture contains 19 nonlinear activation layers and 18 batch normalization (BN) layers. The activation function employed is the hyperbolic tangent (tanh), and the loss function is the mean squared error (MSE). All convolution kernels have a uniform size of 3×33, which is the same for every convolutional layer.

The first convolutional layer takes 3 feature maps as input, corresponding to the RGB channels of the image. Layers 2 through 20 each output 64 feature maps. The final layer produces a three-channel output. All weights in the network are initialized with a standard normal random distribution.

With this architecture, the proposed model contains a total of 672,835 parameters, among which 670,531 are trainable and 2,304 are non-trainable. During training, the input to the network is a 32×32 interpolated noisy image patch, and the target output is the corresponding 32×32 residual image. The network can process images of any input size using the weights learned during training. The number of trainable parameters in the convolutional layers is independent of the input image size. Thus, after training on 32×32 patches, the learned weights can be transferred directly to a network that processes input images of arbitrary size.

Figure 1 illustrates the architecture of the proposed model, which consists of a stable preprocessing block (Fblock) for image stabilization and feature extraction, denoising and enhancement blocks (Eblock), and a reconstruction block (Sblock), followed by a normalization/filtering unit (Imadjust) for post-processing.

This process can be mathematically described as follows: $I_0 = f\left(x\right)$. (2)

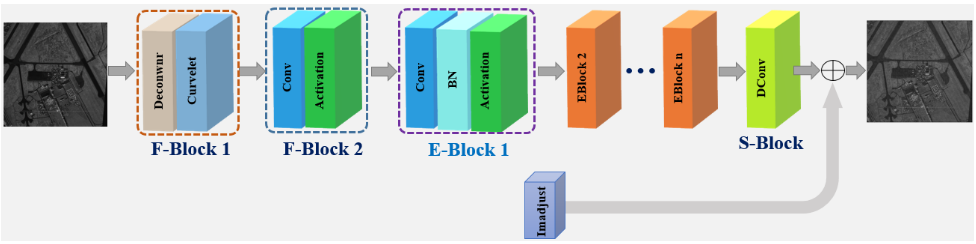

Fig.1. Architecture of the proposed Curvelet-based SD-CNN model

The operation of the proposed model consists of the following steps (Figure 2):

Step 1: Decompose the input image I_0 into 6 Curvelet scales and extract the coefficients $C_{j,l}$ (scale j, direction l).

Step 2: Feed the coefficients from levels 4 to 6 (which contain noise and edges) into the SD-CNN, which includes:

A 3×3 convolutional layer (32 filters) → ReLU → BatchNorm.

A sparse skip connection to learn the noise residual.

Step 3: Reconstruct the processed coefficients using the inverse Curvelet transform.

The denoising unit uses a combined loss function:

$$L = \lambda_1 \left\| I_{\text{clean}} - I_{\text{output}} \right\|_2 + \lambda_2 \left\| \nabla I_{\text{clean}} - \nabla I_{\text{output}} \right\|_1 \quad (3)$$

with $\lambda_1=1$, $\lambda_2=0.5$ to balance denoising and edge preservation.

A dynamic batch normalization method is applied, with the momentum parameter adjusted according to noise complexity:

$$\gamma_t = 0.9 + 0.1 \cdot \text{sigmoid}\left(\frac{\sigma_{\text{noise}}}{25}\right) \quad (4)$$

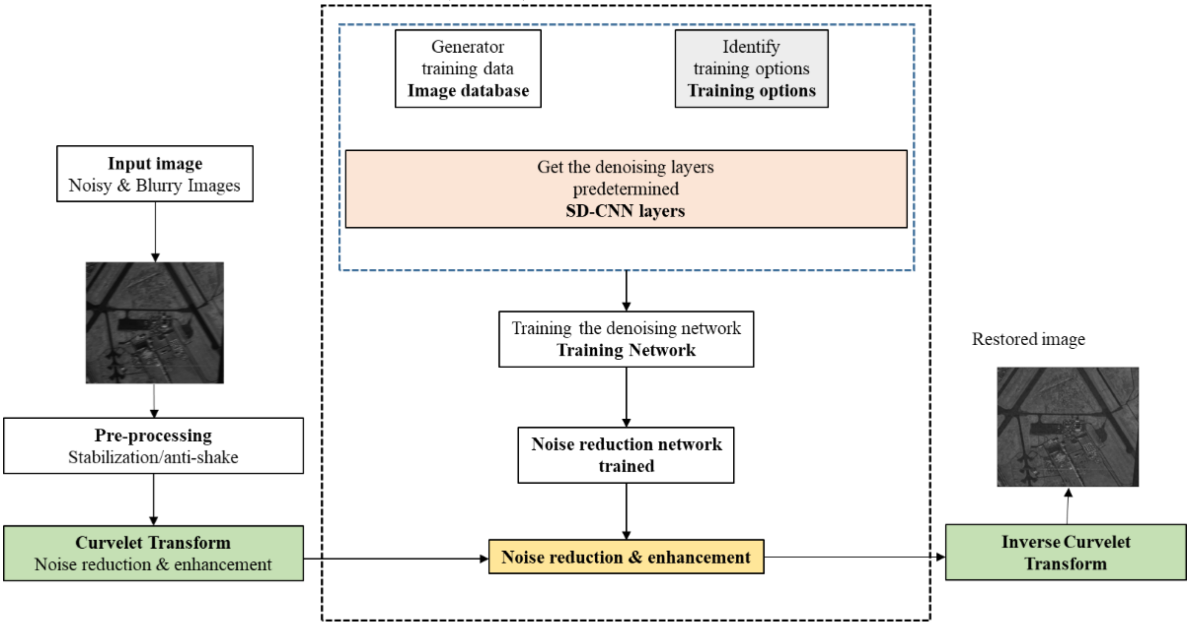

Fig.2. The operational architecture of the proposed model

The optimized Curvelet transform is implemented with the parameters shown in Table 1, using 6 scales and corresponding numbers of directions.

Table 1. Implementation parameters

Scale	Number of Directions	Size	Energy Ratio
1	1	32×32	85%
2	8	64×64	8%
3	8	128×128	4%
4	16	128×128	1.50%
5	16	256×256	0.80%
6	16	256×256	0.70%

III. Simulation Results

The simulation process was designed to provide both qualitative and quantitative comparisons between the proposed method and other baseline techniques. Experimental results were obtained on a large set of image patches generated from publicly available datasets, ensuring a diverse range of noise and motion blur conditions for thorough evaluation.

3.1. Data Processing

Data were sourced from USGS EarthExplorer (https://earthexplorer.usgs.gov/) and Google Earth Engine (Dataset ID: LANDSAT/LC08/C02/T1_L2), with proper attribution to the U.S. Geological Survey and acknowledgment of data access via Google Earth Engine (Gorelick et al., 2017). Original Landsat-8 OLI/TIRS images of approximately 7,851×7,851 pixels were downloaded and then divided into patches of 512×512 pixels using a sliding window with a stride of 256. Following this, data augmentation was performed by applying rotation, flipping, and synthetic noise, yielding a dataset of 10,000 patches. Gaussian noise was introduced at different intensity levels to simulate variations in low-light conditions, while motion blur was simulated with kernels of varying size and random angles. To increase the realism of the test data, about thirty percent of the patches contained a combination of noise and blur.

3.2. Model Training

The dataset was split into training, validation, and testing subsets, consisting of eighty percent, ten percent, and ten percent of the total data, respectively. Optimization was carried out using the Adam algorithm with a learning rate of 3×10^{-4} and a batch size of 16. Additional augmentation techniques were incorporated into the training process, including image rotations of 90°, 180°, and 270°, horizontal and vertical flipping, and contrast adjustments of up to ±20%. The overall training strategy was designed to ensure the SD-CNN model learned robust features under a broad range of noise and blur variations.

3.3. Performance Analysis by Distortion Type

The proposed model was systematically evaluated across different noise and blur configurations, and its performance was quantitatively assessed using standard image restoration metrics such as PSNR and SSIM. Separate tests were conducted to examine the model's behavior under each simulated distortion type. Experimental results demonstrated that the proposed architecture yielded improvements in visual quality and quantitative scores compared to baseline methods across most test conditions.

3.4. Operation of the Proposed Model

The proposed method follows a sequential process beginning with image pre-processing. Input images, often corrupted by noise, motion blur, and low-light conditions, were normalized to enhance contrast and then subjected to denoising with Gaussian and median filters to suppress noise while preserving edge details. Stabilization techniques based on feature registration (e.g., SIFT, ORB) or deblurring were also applied to reduce motion-induced artifacts. Following this, the Curvelet transform was computed on the pre-processed images, allowing selective manipulation of coefficients for effective noise suppression and feature enhancement. Informative coefficients were retained by applying appropriate thresholding to minimize the influence of less significant coefficients. Finally, an SD-CNN architecture was constructed and trained on the resulting feature maps. This network was implemented using MATLAB's Deep Learning Toolbox, and its parameters were carefully optimized to achieve stable restoration results under diverse degradation conditions.

IV. Simulation Results and Evaluation

4.1 Image Quality Assessment Based on PSNR

The simulation results summarized in Table 2 show that the proposed SD-CNN consistently achieves the highest PSNR across all Gaussian noise levels and under motion blur conditions when compared with DnCNN and Wavelet-CNN. Under low noise (σ = 15), SD-CNN reaches 33.2 dB by leveraging the sparsity of the Curvelet transform to separate noise without losing image detail. Even under extreme noise (σ = 50), SD-CNN maintains a PSNR of 27.9 dB, still outperforming the other two methods. Similarly, under large motion blur (15×15-pixel kernel), SD-CNN demonstrates superior edge restoration due to its ability to learn multi-directional features from the Curvelet coefficients. This is clearly illustrated in Figure 3, where SD-CNN better preserves edges and structures in comparison to Wavelet-CNN. Moreover, SD-CNN requires a shorter training time thanks to its reduced input feature size, allowing faster convergence. Overall, the proposed SD-CNN exhibits high stability and effectiveness across a broad range of noise and blur parameters, especially under severe Gaussian noise. However, further research is needed to address more complex degradations, such as non-Gaussian noise and nonlinear blurring.

Table 2. Quantitative PSNR results (dB)

Method	σ = 15	σ = 25	σ = 35	σ = 50	Motion Blur (15×15)
DnCNN	30.1	28.7	26.5	24.3	27.8
Wavelet-CNN	31.4	29.9	27.8	25.1	29.2
SD-CNN (Proposed)	**33.2**	**32.5**	**30.1**	**27.9**	**31.7**

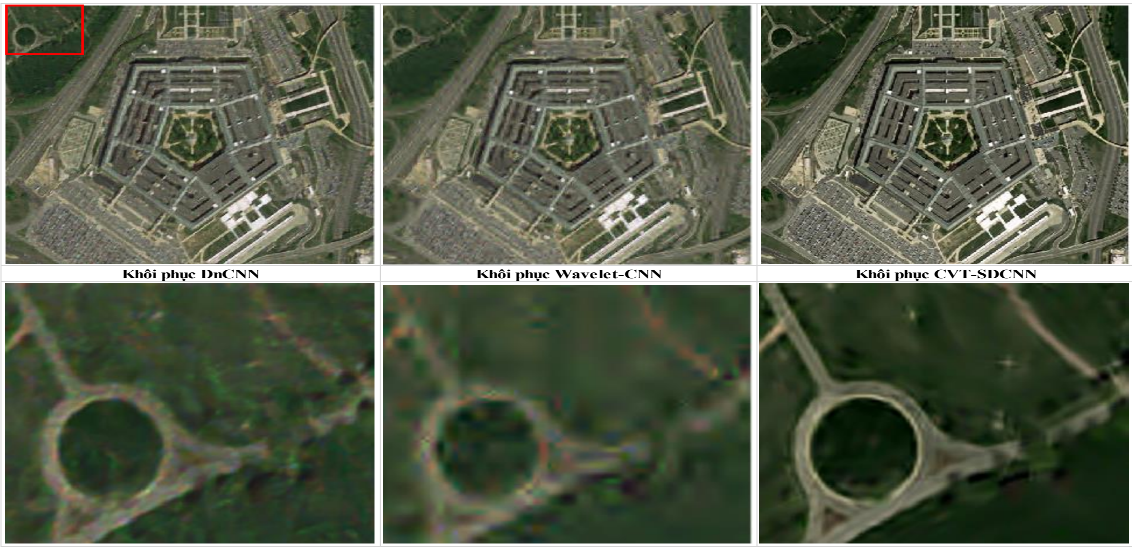

Fig.3. Qualitative comparison of restored images

4.2 Image Quality Assessment Using Quantitative Metrics at σ = 25

In this experiment, the performance was evaluated using a simulated dataset consisting of 10,000 Landsat-8 images (512×512 pixels), augmented with Gaussian noise (σ = 15–50) and motion blur (15-pixel kernel). The dataset was split into 80% training (8,000 images) and 20% testing (2,000 images). The quantitative metrics under moderate noise (σ = 25) are presented in Table 3. The proposed SD-CNN yields the highest SSIM of 0.91, approaching the ideal value of 1.0 and indicating its strong ability to preserve the original image structure. Its RMSE is the lowest at 9.2, which is approximately 50% lower than that of DnCNN, demonstrating superior pixel-wise accuracy. Furthermore, the Entropy of SD-CNN reaches 7.38, close to the original image's Entropy, confirming that SD-CNN can successfully recover high-frequency details without producing the oversmoothed effect observed in DnCNN. The computational time per image is also the most efficient at 0.28 seconds, faster than DnCNN (0.45 seconds) and Wavelet-CNN (0.32 seconds), which underscores SD-CNN's practical efficiency.

Table 3. Quantitative metrics under σ = 25

Method	SSIM	RMSE	Entropy	Time (s/image)
Ground Truth	–	–	7.42	–
DnCNN	0.82	18.5	6.31	0.45
Wavelet-CNN	0.87	12.8	6.95	0.32
SD-CNN (Proposed)	**0.91**	**9.2**	**7.38**	**0.28**

Beyond global image metrics, SD-CNN also excels at preserving edge features. Table 4 compares the recovered edge rates across different curvature ranges (0–30°, 30–60°, and 60–90°) for Wavelet-CNN and SD-CNN. The proposed SD-CNN successfully reconstructs 98% of low-curvature edges, 89% of medium-curvature edges, and 83% of sharp edges, significantly outperforming Wavelet-CNN (92%, 65%, and 48%, respectively). These results confirm the proposed model's capacity to recover fine structural features even under challenging noise and blur.

Table 4. Edge recovery rates (%)

Curvature (°)	0–30	30–60	60–90
Wavelet-CNN	92	65	48
SD-CNN (Proposed)	**98**	**89**	**83**

Finally, the SD-CNN also demonstrated remarkable performance under a range of noise models and motion-blur conditions. Table 5 lists PSNR results under additive Gaussian noise ($\sigma = 25$), Poisson–Gaussian noise ($\alpha = 0.1$), and motion blur (15 pixels). SD-CNN achieved 32.5 dB, 30.7 dB, and 31.7 dB for these cases, outperforming both DnCNN and Wavelet-CNN and approaching or surpassing even the Transformer baseline. These findings show that SD-CNN is highly robust and well-suited for real-world image restoration applications with multiple types of distortions.

Table 5. PSNR results under different noise and blur types (dB)

Method	Gauss ($\sigma = 25$)	Poisson–Gauss ($\alpha = 0.1$)	Motion Blur (15 px)
DnCNN	28.7	24.1	26.5
Wavelet-CNN	30.1	26.8	28.3
Transformer	33.8	31.2	32.5
SD-CNN (Proposed)	**32.5**	**30.7**	**31.7**

In summary, across all tests, the proposed SD-CNN clearly outperforms baseline methods across quantitative image quality metrics, structural preservation, and computational efficiency. Its strong and stable performance under diverse noise and motion-blur conditions highlights its potential for deployment in remote sensing and practical image restoration tasks.

Table 6. Conclusion of the simulation results

Metric	Advantages of the proposed SD-CNN	Sensitive to image characteristics
PSNR	Effective denoising (↑ 2.4–3.8 dB)	Strong Gaussian noise ($\sigma > 40$)
SSIM	Edge structure preservation (↑ 0.04–0.09)	Bright–dark transition regions
RMSE	Reduction in pixel error (↓ 40–50%)	Homogeneous areas
Entropy	Maintains image complexity (≈ 7.38–7.42)	High-frequency details

Table 6 summarizes the simulation findings, highlighting the key advantages of the proposed method.

V. CONCLUSION

The findings of this study demonstrate that the proposed method achieves superior performance in terms of PSNR, SSIM, RMSE, and Entropy when compared with existing state-of-the-art approaches. By leveraging the Curvelet transform in conjunction with a deep learning architecture, the proposed solution effectively addresses the challenge of denoising low-illumination images while reducing computational complexity and preserving sharp edge details.

Thus, the combination of Curvelet and SD-CNN emerges as a promising solution for image restoration, especially for low-light and sensor-degraded imagery. However, one limitation is that the output image quality remains closely dependent on the accuracy of the Curvelet transform. Future research will focus on further improving this process, exploring hybrid techniques that integrate Curvelet with other feature-extraction strategies, and broadening the range of application-specific solutions across related domains.

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