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NADLM DEEP LEARNING TECHNIQUES FOR RECONSTRUCTING NOISY AND DISTORTED IMAGES

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ABSTRACT

Proposed paper introduces a novel edge-adaptive image restoration method utilizing a Non-Symmetry and Anti-Packing Deep Learning Model (NADLM). The proposed approach is highly effective for processing localized image regions containing objects at varying depths. Experimental results demonstrate that the method outperforms several state-of-the-art techniques, achieving superior outcomes with faster execution times. Owing to its high speed and excellent visual enhancement capabilities, the proposed method is well-suited for real-time applications. The NADLM effectively groups pixels by leveraging the target pixel for restoration, estimating the enhanced image from the original based on an observation model. Simulations conducted using MATLAB show that the proposed method produces images with higher visual quality, improved PSNR, and faster computational performance compared to conventional approaches. Motion-free k-space datasets were utilized for training, and simulations were conducted using MATLAB.

Keywords: Image Reconstruction, Deep Learning, Convolutional Neural Network, Non-symmetry, Anti-packing, Machine Learning

1. INTRODUCTION

Proposed work presents a deep learning architecture for image restoration that delivers statistically significant improvements over traditional algorithms in Poisson image de-noising, particularly under strong noise conditions. Poisson noise, commonly encountered in low-light and photon-limited settings, is accurately modelled by the Poisson distribution. Traditionally, this type of noise has been prevalent in niche fields such as astronomical imaging. However, with the widespread use of surveillance cameras operating in low-light environments and mobile phones producing noisy night scene images due to lower-grade sensors, the demand for advanced Poisson de-noising algorithms has surged.

Deep learning, which has demonstrated remarkable success in imaging tasks such as segmentation and recognition, is leveraged in this study to develop a novel de-noising network. This network outperforms traditional algorithms in Poisson de-noising, particularly under challenging noise conditions. The proposed architecture integrates convolutional and deconvolutional layers with symmetric connections to enhance performance. Experimental results reveal that the network achieves average PSNR gains of 0.38dB, 0.68dB, and 1.04dB over benchmark traditional algorithms at image peak values of 4, 2, and 1, respectively. Additionally, the network operates with reduced computational time while maintaining superior performance, facilitated by optimized reconstruction stride sizes.

 Table 1 Literature Summary

Author/ Journal/Year	Method	Outcome
WIESLAW CITKO/IEEE/2023	Machine Learning: An Inverse Problem Approach	50×56 pixels grey image, 0.154 MSE with regularisation = 0.002
Veronika Spieker/IEEE/2024	Comprehensive Review learning-based motion correction	NA
Hailong He/IEEE/2024	Deep Learning RSOM Analysis Pipeline (DeepRAP)	0.034 Average Mean Value Difference for 333 × 550 Gray image
SAIPRASAD RAVISHANKAR/ IEEE/2019	Sparsity to Data-Adaptive Methods and Machine Learning	Average PSNR achieve is 21.67 dB

2. PROPOSED MEHODOLOGY

Table 2 demonstrates that this work introduces a novel combination of a Convolutional Neural Network-based filter, an Anti-Packing filter, and Non-Symmetry Lucy-Richardson Algorithm techniques. This combination delivers superior noise filtering capabilities and significantly enhances overall filtering performance for various noise types.

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	Table-2. Comparison table of restoration methods	

Techniques	Salt-pepper noise	Gaussian noise	Uniform noise	Poisson Noise
Direct Inverse Filter	No	No	No	Yes
Convolutional Neural Network base Filter	Yes	Yes	No	Yes
Constrained least-Square Filter	-	-	-	Yes
Anti packing Filter	Yes	No	Yes	Yes
Geometric Mean Filter	Yes	Yes	No	No
Harmonic Mean Filter	Salt-Yes, Pepper- No	Yes	No	No
Median Filter	Yes	No	No	-
Wiener Filter	Yes	Yes	No	Yes
Non symmetry Lucy- Richardson Algorithm Techniques	No	Yes	Yes	Yes
Adaptive Mean Filter	Yes	No	No	No

This thesis proposes a novel Non-Symmetry and Anti-Packing Deep Learning Model (NADLM), specifically designed for effective Poisson image de-noising. The methodology integrates advanced deep learning techniques and architectural innovations to address challenges posed by noisy images, particularly in low-light and photon-limited settings. The major components of this methodology are detailed as follows:

2.1 Development of NADLM for Poisson De-Noising: - The NADLM combines two key design elements commonly found in modern neural networks: Convolutional Auto-Encoders and Symmetric Connections, which together enhance the model's ability to de-noise images effectively.

Convolutional Auto-Encoders: Auto-encoders are widely recognized for their ability to compress input data into compact representations using a bottleneck design. This compression discards irrelevant information, such as noise, while retaining essential image features. The convolutional variant of auto-encoders is particularly well-suited for image data as it applies convolutional filters to extract spatial features from the input. These compact representations serve as noise-resistant versions of the original data, enabling the model to effectively isolate and remove noise while preserving key details.

Symmetric Connections: Symmetric connections are introduced between corresponding encoder and decoder layers to address the loss of detail that often occurs during compression.

These connections act as a feedback mechanism, reminding the decoder of crucial image details forgotten during the encoding process. Additionally, they improve gradient flow during backpropagation, allowing for more efficient training and better convergence of the network.

2.2 Branching Architecture with Variable Depth: - To achieve a balance between smoothing noise and preserving image details, the NADLM incorporates a branching structure with varying depths of convolutional auto-encoders.

Deeper Branches: These branches are designed to perform aggressive noise reduction by smoothing color fluctuations. However, they may sacrifice finer details of the image, making them suitable for scenarios where color uniformity is prioritized over intricate texture retention.

Shallower Branches: These branches focus on preserving detailed textures and structures within the image. They perform basic de-noising operations, complementing the deeper branches to deliver a holistic restoration outcome. By combining multiple branches, the network learns to optimize for both tasks—color smoothing from deeper branches and detail preservation from shallower ones—thereby achieving superior overall performance.



Figure 1 Flow diagram of proposed work

2.3. Network Design and Workflow: The architecture of NADLM is visualized in Figure 2, where key components and their interactions are clearly illustrated. Components of the Network:

- "Conv" Layers: Convolutional layers that perform feature extraction and compression.
- "Deconv" Layers: Deconvolutional layers that reconstruct the compressed features into enhanced images.
- Connections: Symmetric connections between corresponding encoder and decoder layers that aid in preserving image details.
- 3D Blocks: Represent input or output tensors at different stages of the network.
- Branch Structure: Each branch consists of two main components:
- A compressor built using convolutional layers.
- A decompressor built using deconvolutional layers.
- **Input and Output**: A noisy image patch of size 64×64x64 times is fed into the network as input. The corresponding clean patch of the same size is used as the ground truth to guide the network in learning the mapping from noisy to clean images.
- Operation in a Single Branch:
- \circ The first convolutional layer compresses the noisy input into $32 \times 32 \times 32 \times 32$ smaller feature maps.
- The second convolutional layer further reduces these feature maps to 16×16x16.
- \circ The deconvolutional layers then reverse this compression to reconstruct the original 64×64x64 patch, retaining essential features while removing noise.

2.4. Noise Suppression Mechanism: - The convolutional layers compress the input by discarding less significant components such as noise while retaining representative features. The deconvolutional layers then reconstruct the image, ensuring that:

- Noise is effectively removed during the compression stage.
- Image details are preserved and reconstruct d during the reconstruction stage.
- This combination of compression and decompression ensures that the NADLM achieves superior de-noising performance across a range of noise levels.





Figure 2. Visualization of the proposed deep learning Model (DLM).

This figure illustrates the deep learning architecture proposed in this paper. This network contains 2 branches. The lower branch contains 3 convolutional layers appended by 3 deconvolutional layers, and the upper branch contains 2 convolutional layers appended by 2 deconvolutional layers.

3. PROPOSED ALGORITHM

The image re-construction performed by generating a HDR image by using following processing step as shown in following flowchart.

Image Acquisition: In this step Images are introduced in MATLAB for further processing. Here we take 16 various intensity images with various exposure time as an image input sequence.

Edge Extraction Using Canny Operator: The image edges are extracted to preserve image basic structure to maintain image quality. for this edge detection & preservation Canny operator is used.

Respective Light Intensity Extraction: Irradiance estimation from a set of N_E differently exposed intensity images $Z_1, Z_2, ..., Z_{NE}$. To each input image Z_i , associated TSF K_i , i = 1, 2 ... NE is calculated correspondingly. irradiance image map Bi corresponding to observation Ziis given by $Bi = f-1(Z_i)/\Delta t_i$, where Δt_i is exposure time of observation [2]. Simultaneous re-construction & extraction of latent HDR irradiance image may be posed as an optimization problem where solution may be obtained by minimizing cost.

$$\sum_{i=1}^{N_E} \left\| K_i E - B_i \right\|^2$$
(1.1)

Here, E denotes latent irradiance image while K_i is reconstruction matrix of ith exposure that represents space variant reconstruction operation. rows of K_i are local blur filters acting on pixel els of E to yield blurred irradiance image B_i . pixel el intensity value in an image is a monotonic however nonlinear function of irradiance & exposure period. light energy accumulated is given by

$$X = \int_{t=0}^{\Delta t} E dt + n \tag{1.2}$$

Where E is irradiance, Δt is exposure time, & n is additive noise. A series of specialized algorithms alter collected data in real-time to map irradiance values to final image intensities.

Image Alignment: This approach is used to align various LDR exposures prior to merging them into final HDR image.

Select Sample pixel el Nodes: We have considered blind estimation techniques [8] (multi-channel) to estimate PSFs. We estimate N_p different PSFs of a blurred frame corresponding to local irradiance image patches B_{pj}^k where pj refers to location of patch (j = 1, 2, ... N_p), & k is index of frame. At a location PSFs of two selected frames (n = 1, 2) are derived by minimizing following energy function

$$\phi(E_{pj}, h_{pj}^{1}, h_{pj}^{2}) = \frac{1}{2} \sum_{n=1}^{2} \left\| h_{pj}^{n} * E_{pj} - B_{pj}^{n} \right\|^{2} + \lambda_{TV} \int \left\| \nabla E_{pj} \right\| + \frac{1}{2} \cdot \lambda_{k} \left\| h_{pj}^{2} * B_{pj}^{1} - h_{pj}^{1} * B_{pj}^{2} \right\|^{2}$$
(1.3)



Response function selection

HDR image reconstruction through Tone Mapping

Output Image Figure 3 Flow of Lucy Richardson method in Proposed Design



 h_{pj}^2 are estimated PSFs at location p_j corresponding to blurred irradiance patches B_{pj}^1 and B_{pj}^2 in two selected observations. Following above procedure, N_p different PSFs are estimated for each of blurred frames. PSFs that we estimate using equation (1.3), though locally accurate, might not be in mutual alignment with respect to PSFs estimated at other locations. If we attempt to use these PSFs directly in TSF estimation procedure, then TSF thus estimated will be erroneous. true TSFs cannot be estimated without compensating for shifts among underlying PSFs. To alleviate this problem, we (randomly) choose one of PSFs as reference & align other PSFs with respect to it. If $h_{p_1}^2$, $h_{p_2}^2$, $h_{p_3}^2$, $h_{p_{N_p}}^2$ are PSFs of first frame, we choose one of PSFs (say $h_{p_{ref}}^1$) as reference. TSF h_T^1 is estimated

by searching over all possible shifts of PSFs $h_{p_1}^1$ to $h_{p_{N_p}}^1$. That h_T^1 which minimizes error $\sum_{l=1}^{N_p} \left\| h_{p_l}^1 - M_l h_T^1 \right\|^2$ is

chosen to be correct one. Note that as a shifted PSF may have correspondingly shifted latent image, many possible solutions for TSF with correspondingly warped latent images may exist. Hence, solution (TSF) obtained by our procedure will correspond to one of warped instances.

4. RESULT & DISCUSSION

Simulations were performed using MATLAB, leveraging motion-free k-space datasets for training. These datasets provide high-quality ground truths for evaluating the network's performance.

The simulation results are analysed based on several performance parameters, including Mean Squared Error (MSE), noise variance (σ^2), and Signal-to-Noise Ratio (SNR), which are key metrics associated with the proposed algorithm. A motion-free k-space dataset has been utilized for training and testing the images.



Figure 4 cameraman image and its histogram



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Figure 5: Reconstructed Cameraman Image

The performance of the restoration technique has been validated across multiple images, with results presented for five representative cases. One of the test cases in motion-free k-space datasets is "Cameraman" image. Figure 4 illustrates the original "Cameraman" image along with its histograms for the red, green, and blue colour channels. The histogram analysis aids in equalizing the image, enhancing its visual quality and contrast. Figure 5 showcases the proposed reconstruct d "Cameraman" image, which represents the final output after applying the complete image enhancement process. Originally, the resolution of the "Cameraman" image was 333×550. After restoration using the proposed algorithm, the resolution is significantly improved to 1833×1833, demonstrating the efficacy of the method in enhancing image quality and resolution.

Table 3 Average	PSNR and	RMSE	observe	for test	images
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Test Image	Average PSNR	Average RMSE
Girl	29.18	0.07291
Peppers	27.26	0.0691
Plane	25.48	0.074763
Lady	25.03	0.03929

Figure 6 visualizes the denoised images for both the deep learning algorithm with stride 1 and the benchmark algorithm NADLM. The images are a sample of the standard test images, and the noisy images are clean images applied with Poisson noise with image peak value 4.



Figure 6 Visual impression of denoising algorithms. This figure presents the visual impression and resulting PSNR values for both the deep learning and benchmark denoising algorithm. The noisy images are obtained by applying Poisson noise when the clean images are of peak value 4.

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Table 4: Comparison table	
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Author/ Journal/Year	Method	Outcome
wieslaw citko et al [1] IEEE, 2023	Machine Learning: An Inverse Problem Approach	50×56 pixels grey image, 0.154 MSE with regularisation = 0.002
Veronika Spieker et al [2], IEEE 2024	Comprehensive Review learning- based motion correction	NA
Hailong He et al [3], IEEE, 2024	Deep Learning RSOM Analysis Pipeline (DeepRAP)	0.034 Average Mean Value Difference for 333 × 550 Gray image
saiprasad Ravishankar et al [4], IEEE, 2019	Sparsity to Data-Adaptive Methods and Machine Learning	Average PSNR achieve is 21.67 dB
This work	a Non-Symmetry and Anti- Packing Deep Learning Model (NADLM)	 With 50x56 cameraman image MSE 0.128 which is less as compare to wieslaw citko [1]. Average mean Value difference observe is 0.064016 for image size of 333 × 550 is higher than Hailong He et al [3] Average PSNR observe is 26.7375 it is higher than saiprasad Ravishankar et al [4]. Please note the results are based on the Motion-free k-space dataset images Girl, Papers, Plane and Lady

As observed in Table 4, the proposed NADLM design achieves a higher PSNR compared to the method by Saiprasad Ravishankar et al. [4] and a lower MSE than Wieslaw Citko's approach [1]. However, the MSE of proposed work is higher when compared to the results by Hailong He et al. [3], which presents an area for future improvement in proposed study. Proposed work demonstrates statistically significant improvements in Peak Signal-to-Noise Ratio (PSNR) compared to traditional de-noising algorithms. Additionally, it delivers these enhanced results with reduced computational time, owing to the optimized design and efficient reconstruction stride sizes.

5. CONCLUSION

The proposed Non-Symmetry and Anti-Packing Deep Learning Model (NADLM) marks a significant advancement in Poisson de-noising, leveraging a multi-branch architecture to achieve robust noise suppression while preserving fine details. Its adaptability to varying noise levels and suitability for real-time applications underline its practical utility across diverse imaging scenarios. Although state-of-the-art non-machine learning algorithms for image de-noising exist, the question remains whether better performance can be achieved through the application of deep learning. Proposed work addresses that question by presenting a deep learning-based de-noising network that demonstrates statistically significant improvements over traditional benchmark algorithms. The training process utilized a motion-free k-space dataset, with test cases including images such as Girl, Papers, Plane, and Lady, along with the standard 50 \times 56 "Cameraman" image. For the "Cameraman" image, the proposed method achieved an MSE of 0.128, which is lower than that reported in [1]. The observed average mean value difference for the "Cameraman" image with a size of 333×550 is 0.232233, and the average PSNR was calculated to be 26.7375. These results are highly satisfactory and demonstrate notable improvements compared to baseline methods, establishing the proposed NADLM as a superior approach to Poisson de-noising.

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