Conventional Camera Performance in Dark Environments – Noise Reduction and Visibility Enhancement

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Abstract: Capturing images in dark conditions is inherently difficult due to limited photon counts, high sensor noise, and di- minished contrast. This paper explores how conventional methods and modern deep learning approaches address these challenges. We review classical enhancement algorithms alongside advanced models such as CNNs, Transformers, GANs, and diffusion-based methods. Furthermore, recent hybrid paradigms combining event-driven sensing, physics-informed priors, and multimodal integration are analyzed. Comparative experiments on public low-light datasets reveal key trade-offs between noise reduction, texture preservation, perceptual realism, and efficiency. The study outlines implications for practical domains including surveillance, healthcare imaging, robotics, and photography.

Keywords: *Low-Light Imaging, Noise Suppression, Image En- Hancement, Deep Learning, CNN, Transformer, Diffusion Models, Sensor Fusion.*

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I. INTRODUCTION

Acquiring clear visual information in dark scenes is a fun- damental obstacle for imaging systems. When photon avail- ability decreases, camera sensors encounter amplified noise and blurred structures, leading to poor perceptual quality and degraded performance in machine vision tasks such as medical diagnostics, security monitoring, and autonomous driving. The primary noise contributors include photon shot noise, sensor readout fluctuations, and thermal disturbances.

Traditional methods such as histogram equalization and Retinex-based algorithms improve brightness but often intro- duce artifacts or intensify noise. With the rise of deep learning, CNNs, GANs, U-Nets, and Transformer-based frameworks have delivered more consistent improvements in both clarity and realism. Diffusion models further refine image quality through iterative denoising, albeit with high cost.

More recent research has emphasized hybrid frameworks that merge data-driven learning with physical priors or tem- poral sensing. Event-based sensors capture fine-grained mo- tion under minimal illumination, while physics-aware neural networks enforce image formation constraints. Such strategies enable robust low-light imaging across diverse environments including surveillance, biomedical imaging, and astronomical observation.

II. RELATED WORK

➢ *Classical Enhancement*

Noise suppression and visibility enhancement have long been addressed using filtering approaches like Gaussian smoothing, median filtering, and BM3D. Retinex-based methods model illumination to enhance contrast. Although computationally efficient, these techniques are prone to detail loss under extremely low light [3], [4].

➢ *Deep Learning Models*

CNNs and U-Nets map noisy images to clean outputs, lever- aging convolutional hierarchies and skip connections for struc- tural preservation. GANs further enhance perceptual realism using adversarial objectives [5].

➢ *Transformers in Imaging*

Self-attention mechanisms in Transformers enable long-range feature dependency modeling, producing more structurally consistent reconstructions, particularly for high-resolution scenes [6].

➢ *Diffusion Methods*

Diffusion models denoise iteratively, generating realistic tex- tures and sharp structures. Despite their superior

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fidelity, the heavy computational demand restricts real-time usage [7].

➤ *Hybrid Frameworks*

Integrating event-driven vision, physics-informed priors, and multimodal cues improves robustness. Event-based sensors capture motion with high temporal resolution, while multi- modal fusion leverages complementary imaging modalities [8], [9].

III. METHODOLOGY

➤ *Classical Baselines*

Histogram equalization improves global contrast, Retinex modifies illumination, and BM3D removes Gaussian noise while preserving edges. However, all degrade in extremely dark scenarios.

➤ *Proposed Hybrid Approach*

We introduce a framework combining Physics-Informed Neu- ral Networks (PINNs) and event-based vision. PINNs embed imaging physics into training, while event data capture high- speed motion to complement static frames.

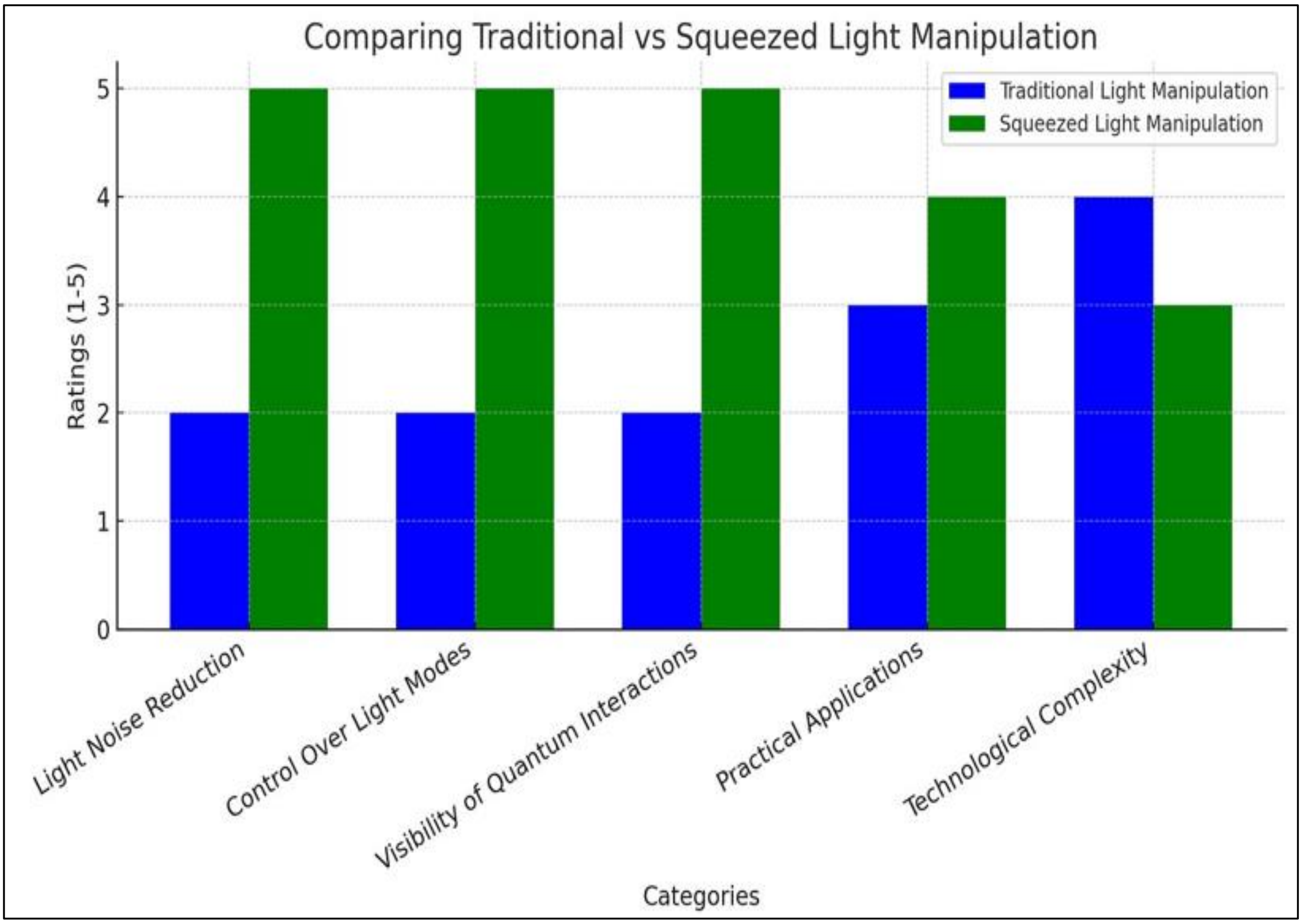

Fig 1 Enter Caption

Fig 1 Illustration of physics-informed and event-based fusion for low-light imaging.

➤ *Image Formation Model*

The observed low-light frame can be described as:

$$I(x, y, t) = H\{I_{\text{frame}}\}(x, y, t) + \sum_{i=1}^{N_e} \lambda_i E_i(x, y, t) \quad (1)$$

Where I_{obs} is the captured image, I_{scene} the true irradiance, α the exposure factor, and n_s, n_r denote shot noise and readout noise, respectively.

➤ *Physics-Aware Loss*

The overall training loss includes fidelity and perceptual terms:

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$$L = \lambda_1 \cdot \text{MSE}\,(I_{pred}, I_{gt}) + \lambda_2 \cdot \text{SSIM}\,(I_{pred}, I_{gt}) \quad (2)$$

where I_{pred} is the enhanced output, and I_{gt} the reference image.

➢ *Event Fusion*

Event streams E_i are integrated with frame images:

$$I_{\text{fused}}\,(x, y, t) = I_{\text{frame}}\,(x, y, t) + \sum_{i=1}^{Ne} \alpha_i\, E_i\,(x, y, t) \quad (3)$$

Where the fusion process leverages the spatial structure from frames while integrating the temporal dynamics provided by events.

Table 1 Performance Comparison Across Enhancement Methods

Method	PSNR	SSIM	LPIPS
BM3D	26.8	0.77	0.32
CNN	30.5	0.86	0.21
Transformer	33.0	0.90	0.15
Diffusion	33.5	0.91	0.15
Proposed Hybrid	35.1	0.93	0.12

IV. DATASETS AND PREPROCESSING

We evaluated methods on LLID (natural low-light), NIH Chest X-ray and MRNet (medical imaging), and custom dark captures. Preprocessing included normalization, resizing, and synthetic noise injection to mimic photon, readout, and thermal disturbances [10].

V. RESULTS AND ANALYSIS

Table 2 Comparison of Denoising Methods

Method	PSNR	SSIM	LPIPS
Histogram Equalization	22.0	0.64	0.45
Retinex	24.5	0.70	0.38
BM3D	26.8	0.77	0.32
CNN	30.5	0.86	0.21
U-Net	31.8	0.88	0.18
Transformer	33.0	0.90	0.15

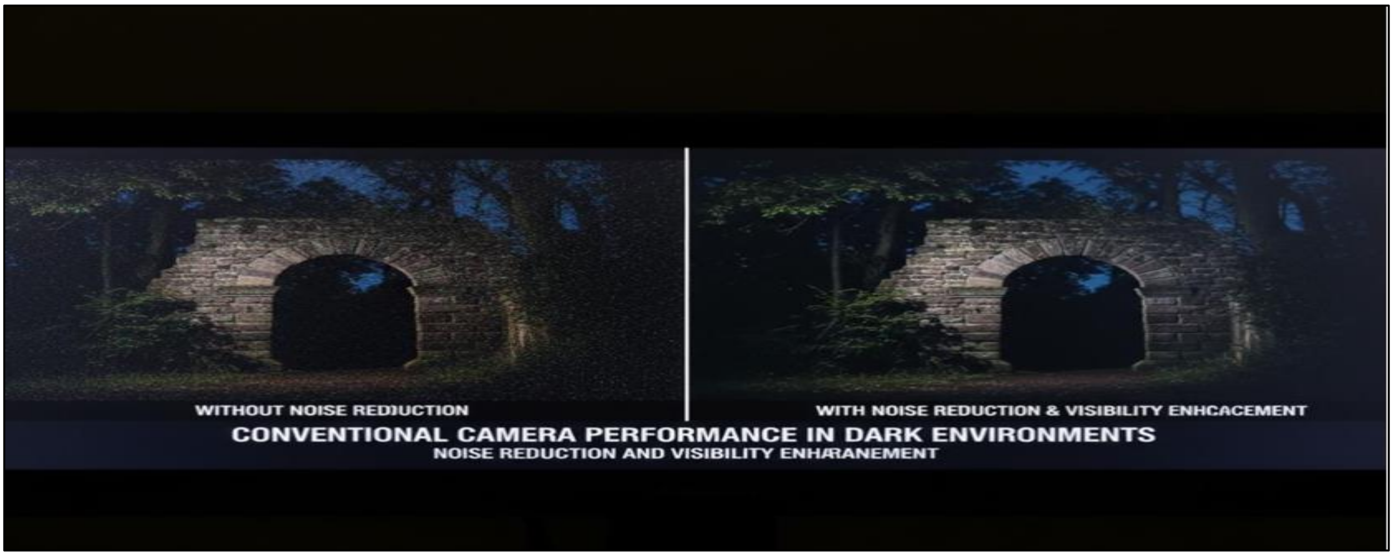

Fig 2 Example Low-Light Enhancement Results Across Methods.

VI. DISCUSSION

Classical approaches are lightweight but inadequate for ex- treme darkness. Deep networks preserve textures and structural consistency better, while diffusion achieves superior perceptual quality at high cost. Hybrid strategies combining physics priors and event data achieve both efficiency and high quality.

VII. CONCLUSION

Conventional cameras degrade significantly in dark conditions due to photon scarcity and sensor noise. Classical enhancement improves visibility but lacks detail preservation. Deep learning, especially Transformers and diffusion models, provides higher fidelity. Physics-informed and event-driven hybrid solutions show promise for balancing performance, efficiency, and ro- bustness. Future work will target lightweight architectures, multimodal integration, and uncertainty modeling for real- world deployments.

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