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ENHANCED NIGHT VISION IMAGE PROCESSING ALGORITHM FOR AUTONOMOUS ROBOTS: INTEGRATING DIFFUSION MODELS AND ADAPTIVE OPTIMIZATION

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A B S T R A C T

Autonomous robots operating in low-light or under- water environments face significant challenges due to reduced visibility, high noise levels, and dynamic environmental conditions. These limitations hinder critical tasks such as navigation, object detection, and surveillance. Existing night vision image processing methods struggle with noise suppression, illumination variability, and the complexities of blind inverse problems, where both the observed image and the transformation model are partially or entirely unknown. This paper presents a novel algorithm that integrates variance-preserving diffusion models with adaptive optimization techniques to enhance night vision image processing. The proposed approach combines learned diffusion priors for noise suppression with joint optimization of forward model parameters and latent image reconstruction, effectively addressing the challenges of underwater imaging. This paper mainly focuses on Noise Mitigation while preserving fine structural details in low-light images, Dynamic Illumination Adaptation adjusting to varying illumination conditions in real-time. Forward Model Variability Management to mitigate motion blur, sensor imperfections, and light attenuation. Extensive experiments demonstrate the algorithm's superiority over state-of-the-art methods, achieving up to 20% improvement in Peak Signal-to-Noise Ratio (PSNR) and 15% in Structural Similarity Index (SSIM). This work represents a significant advancement in enabling robust and reliable autonomous operations in challenging low- light environments.

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1. INTRODUCTION

1.1 Background and Motivation

The ability of autonomous robots to operate effectively in low-light or underwater environments is crucial for a range of applications, including surveillance, exploration, and industrial automation. However, these environments present significant challenges for vision-based systems due to reduced visibility, high noise levels, and the dynamic nature of illumination and environmental conditions. In underwater scenarios, these challenges are further exacerbated by factors such as scattering, light attenuation, and sensor imperfections. Such limitations often lead to degraded image quality, which compromises the robot's ability to make accurate real-

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time decisions. Current approaches to night vision and underwater image processing often rely on traditional denoising or enhancement algorithms. While effective in specific cases, these methods struggle to handle the complexities of blind inverse problems, where both the observed image and the forward model governing image formation are partially or entirely unknown. Additionally, these methods often lack adaptability, failing to account for variability in illumination, motion blur, and sensor noise. As a result, there remains a pressing need for robust image processing algorithms that can adapt dynamically to challenging conditions while preserving critical image details.

1.2 Research Objectives

This work aims to address these challenges by introducing a novel algorithm that combines data-driven approaches with physics-based modeling. The primary objectives are:

- To develop a robust image processing pipeline: Capable of suppressing noise, enhancing contrast, and mitigating blur in low-light or underwater environments.
- To optimize forward model parameters adaptively: Handling variations in image formation processes, such as scattering, light attenuation, and sensor imperfections.
- To leverage diffusion-based priors: Ensuring effective noise suppression and structural preservation by incorporating learned priors derived from data.

1.3 Significance of the Study

The proposed algorithm represents a significant advancement in enabling autonomous robots to operate reliably in low-light or underwater environments. It achieves this by:

- Enhancing Adaptability: Simultaneously optimizing latent image reconstruction and forward model parameters, allowing the system to dynamically adapt to changing environmental conditions.
- Improving Image Quality: Leveraging variance-preserving diffusion models to suppress noise while preserving critical structural details, such as edges and textures.
- Broad Applicability: Enabling robust performance in diverse applications, such as underwater navigation, industrial inspection, and disaster recovery operations.

1.4 Novel Contributions

This paper introduces several novel contributions to the field:

- Integration of Variance-Preserving Diffusion Models: To address the complexities of noise suppression and detail preservation in extreme conditions.
- Joint Optimization algorithm: A unified approach for optimizing forward model parameters and latent image quality, addressing variability in image formation processes.
- Real-Time Adaptability: Mechanisms to dynamically ad- just to changes in illumination, motion, and noise levels, ensuring consistent performance in real-world scenarios.

By addressing critical gaps in existing methodologies, this work provides a robust solution for enabling reliable autonomous operations in extreme low-light environments. The remainder of this paper details the proposed algorithm, its mathematical foundations, and experimental validation.

2. RELATED RESEARCH

Current night vision image processing methods face several limitations. Many existing techniques, such as traditional denoising filters and deep learning-based enhancement methods, struggle with noise suppression while maintaining fine structural details. In particular, the presence of photon-starved noise in low-light environments and underwater scattering severely degrades image quality. Real-time processing also remains a challenge due to the computational overhead of advanced models, making them unsuitable for autonomous robotic applications requiring immediate decision making (Alzaga et al., 2025; Rea et al., 2025; Al-hamadani & Al-Darraji, 2025).

Recent advancements, such as diffusion models and adaptive optimization techniques, have demonstrated potential for improved performance. However, most current implementations fail to integrate these two approaches in a unified manner. Additionally, handling complex inverse problems where both the observed image and the transformation model are unknown remains largely unexplored. Our proposed work addresses these gaps by integrating variance-preserving diffusion models with an adaptive forward model optimization strategy to enhance night vision image processing. This literature review examines recent works related to noise reduction, image enhancement, and adaptive optimization methods, with a particular focus on the integration of diffusion models and optimization techniques, as these are key components of the proposed algorithm in this paper.

2.1 Low-Light Image Enhancement and Night Vision Systems:

Low-light image enhancement is a vital area in computer

vision, addressing challenges such as poor visibility and high noise. Zhang et al. (2023) utilized generative adversarial networks (GANs) to develop a model that improves brightness and contrast while preserving details in low-light conditions. Their approach adapts to diverse lighting scenarios, providing visually natural outputs suitable for night vision systems. Zheng et al. (2022) conducted a comprehensive survey, categorizing low-light enhancement methods into histogram- based, Retinex theory-based, and deep learning approaches. Their work highlights deep learning's superiority in handling complex illumination variations, particularly for autonomous and surveillance systems. Yoon and Cho (2023) introduced a method combining contrast enhancement with an adaptive noise attenuator, designed for detecting vehicles under low- light conditions. Their approach enhances image clarity, making it applicable in augmented reality and autonomous driving. Wang, F., et al. (2021) proposed a joint optimization algorithm leveraging multi-scale Retinex theory and frame accumulation, achieving significant improvements in temporal consistency and brightness for video sequences.

2.2 Noise Reduction Techniques:

Noise reduction is integral to image processing, especially in low-light and high-noise environments. Shi and Wang (2024) proposed a pioneering method that combines diffusion model and adaptive enhancement with noise reduction, specifically for low-light video. Their approach preserves critical details while significantly reducing noise, making it ideal for surveillance and low-light applications. Yang et al. (2010) developed an adaptive non-local means (ANLM) filter tailored for denoising live-cell microscopy images. Though intended for biological imaging, this technique is adaptable to low-light scenarios, providing robust noise reduction while preserving fine textures. The anisotropic diffusion method by Perona and Malik (1990) introduced a scale-space algorithm that reduces noise while preserving edges. Its edge-preserving capabilities make it foundational in noise reduction for various imaging conditions, including low-light and underwater environments.

2.3 Adaptive Optimization in Image Processing:

Adaptive optimization techniques dynamically adjust parameters based on image content, enhancing performance across diverse scenarios. Yoon and Cho (2023) employed an adaptive noise attenuator that integrates seamlessly into contrast enhancement workflows, optimizing for varying levels of noise and brightness. Shi and Wang (2024) introduced the Content-Preserving Diffusion Model (CPDM), which enhances underwater images by maintaining critical content while mitigating noise and distortion. This model demonstrates the effectiveness of adaptive optimization in challenging environments. Zhang et al., (2023) presented a multi-scale fusion approach combined with adaptive gamma correction to enhance low-light underwater images. Their technique dynamically adjusts contrast and color balance, overcoming challenges posed by light scattering and attenuation.

2.4 Underwater Imaging Challenges and Solutions:

Under- water imaging suffers from light scattering, absorption, and color distortion. Jiang et al. (2023) addressed these issues using a GAN-based preprocessing algorithm, which restores visibility and enhances color balance. Their method ensures higher- quality images for subsequent analysis or autonomous applications. Ding et al. (2024) reviewed visual-based localization and mapping techniques, emphasizing the importance of clear underwater images for vehicle navigation. Their survey identified the need for robust enhancement methods to improve the accuracy of localization algorithms. Zhang et al. (2023) proposed a multi-scale fusion technique paired with adaptive gamma correction, achieving significant improvements in visibility and color restoration for underwater environments. Similarly, Hu et al. (2024) developed an enhancement algorithm that combines contrast enhancement with dehazing, addressing issues like turbidity and low contrast.

2.5 Real-Time Night Vision for Autonomous Robots:

Real-time night vision systems require efficient algorithms that balance enhancement quality with processing speed. Katkuri et al. (2024) explored deep learning techniques for nighttime vision, highlighting their role in autonomous vehicle navigation. The study emphasized the importance of convolutional neural networks (CNNs) for feature extraction and enhancement in low-light scenarios. Sarode et al. (2020) discussed deep learning approaches for image restoration and enhancement, with a focus on real-time applications. These methods, when integrated with autonomous robots, can significantly improve their perception and decision-making in dark environments. Wang, L., et al. (2024) demonstrated the feasibility of integrating GANs into real-time systems, achieving enhanced brightness and detail in night vision scenarios. The Ding et al. (2024) model's adaptability and low computational overhead make it suitable for robotic applications.

2.6 Metrics for Image Quality Evaluation:

Metrics are crucial for evaluating the effectiveness of enhancement techniques. Wang, Z., et al., (2004) introduced the Structural Similarity Index (SSIM), a widely used metric that measures perceived image

quality based on structural information. It has become a standard for assessing the output of low-light and underwater enhancement algorithms. Moghimi and Mohanna (2021) reviewed underwater image enhancement techniques and compared various metrics, including Peak Signal-to-Noise Ratio (PSNR), SSIM, and Contrast-to-Noise Ratio (CNR). They highlighted the limitations of these metrics, particularly in evaluating perceptual quality, and called for more robust measures tailored to specific applications. Zheng et al. (2022) discussed the trade-offs between computational complexity and accuracy in quality evaluation, advocating for hybrid metrics that combine objective measures with perceptual feedback.

2.7 Applications in Autonomous Navigation and Surveillance:

Enhanced imaging is pivotal for autonomous navigation and surveillance systems. Wang, Y., et al. (2024) proposed a multi-sensor fusion localization method, utilizing enhanced under- water images for accurate vehicle positioning. Their method integrates Unscented Kalman Filter techniques to improve the reliability of underwater navigation. Sarkar et al. (2024) demonstrated the application of UICE-MIRNet-guided image enhancement for underwater object detection. Their approach improves the accuracy of object detection algorithms, making it valuable for underwater surveillance and exploration. Katkuri et al. (2024) emphasized the integration of enhanced nighttime vision systems into autonomous vehicles, highlighting the role of image enhancement in improving navigation accuracy and situational awareness. The Ma et al. (2023) study also explored applications in surveillance, where low-light enhancement improves the reliability of object detection and tracking.

3. PROPOSED WORK

The proposed work enhances image processing in extreme low-light and underwater environments by combining variance-preserving diffusion models with adaptive forward model optimization. It addresses challenges such as noise, motion blur, and dynamic illumination through a unified, data- driven, and physics-based approach.

3.1 Algorithm Overview

The algorithm integrates three core components:

1) Input Preprocessing: Handling noisy, low-light images captured in challenging environments.
2) Diffusion-Based Denoising: Leveraging learned priors to iteratively refine the latent image and suppress noise.
3) Joint Optimization: Simultaneously optimizing forward model parameters and latent image quality to handle variability in image formation.

1) Input Preprocessing: The algorithm processes noisy, blurred, and low-contrast images, y, captured under extreme low-light or underwater conditions. where the key challenges include:

- Noise: Sensor noise, photon starvation, and environmental interference.
- Blur: Motion blur and scattering caused by underwater turbidity.
- Low Contrast: Due to light attenuation and non-uniform illumination.

These inputs are modeled as:

$$y = H_{\varphi}(x) + \eta \tag{1}$$

where:

$H_{\varphi}(x)$: Forward operator describing the image formation process (e.g., blurring, attenuation).

η: Additive noise.

2) Diffusion-Based Model Adaptation: Variance-preserving diffusion models are employed to suppress noise and enhance structural details. The algorithm uses forward and reverse stochastic differential equations (SDEs) to model and refine the image.

Forward Diffusion Process:

$$dx_t = -\frac{\beta(t)}{2} x_t dt + \beta(t)\ dw \tag{2}$$

where:

x_t: State of the image at time *t.*

$\beta(t)$: Noise schedule controlling the diffusion process.

dw: Standard Brownian motion.

Reverse Diffusion Process:

$$dx_t = \left(-\frac{\beta(t)}{2} x_t - \beta(t) \nabla_{x_t}\ log\, p\,(x_t)\right) dt + \beta(t)\ dw \tag{3}$$

where:

$\nabla_{x_t}\ log\, p\,(x_t)$: Gradient of the log-probability density, guiding the reconstruction toward likely clean images.

The reverse diffusion refines the noisy image y into a clean, latent image x by leveraging learned priors.

3) Joint Optimization of Forward Model Parameters and Latent Image: The algorithm jointly optimizes the forward model parameters φ and the latent image x to achieve high- quality reconstructions.

The optimization problem is formulated as:

$$\theta^*, \varphi^* = arg\ \min_{x,\varphi} \frac{1}{2} \left\| H_{\varphi}(x) - y \right\|^2 + R_x(x) + R_{\varphi}(\varphi) \tag{4}$$

where:

- $\left\| H_{\varphi}(x) - y \right\|^2$: Data fidelity term ensuring the reconstructed image matches the observed input.
- $R_x(x)$: Regularization term incorporating diffusion-based priors to preserve structural details.

- $R_\varphi(\varphi)$: Regularization term stabilizing the forward model parameters.

Forward Model Parameter Optimization: Refines φ to address variations in blurring, attenuation, and noise characteristics.

Latent Image Refinement: Iteratively reconstructs x using gradient-based updates informed by data fidelity and priors.

3.2 Workflow and Output

1) Workflow: The proposed algorithm follows a systematic workflow:

i. Preprocessing: Normalize and down sample input images.

ii. Initialization: Set initial estimates for the forward model φ_0 and latent image x_0.

iii. Iterative Optimization:

Update x using:

$$x_{k+1} = x_k - \alpha\left[H_\varphi^T(H\varphi(x_k) - y) + \nabla_x R_x(x_k)\right] \quad (5)$$

Refine φ using:

$$\varphi_{k+1} = \varphi_k - \beta\left[\nabla\varphi H_\varphi(x_{k+1})^T(H_\varphi(x_{k+1}) - y) + \nabla_\varphi R_\varphi(\varphi_k)\right] \quad (6)$$

iv. Convergence Check: Stop iterations when changes in x and φ are below predefined thresholds.

2) Output: The algorithm produces a high-quality reconstructed image x∗ with:

- Suppressed noise.
- Enhanced contrast and sharpness.
- Accurate corrections for blur and attenuation.

3.3 Highlights of the algorithm

- Noise Mitigation: Achieves effective denoising through diffusion priors while preserving fine details.
- Dynamic Adaptation: Adjusts to varying illumination and environmental conditions via forward model optimization.
- Real-Time Capability: Supports fast iterative updates suitable for real-world robotics applications.

4. MATHEMATICAL DERIVATIONS

For the reconstruction of the latent image the proposed work mainly focusing on the forward model, optimization objectives, iterative updates for latent image and forward model parameter refinement.

4.1 Forward Model

The forward model defines the relationship between the observed noisy image$y$, the latent clean image$x$, and the noiseη. It is expressed as:

$$\boldsymbol{y = H_\varphi(x) + \eta} \quad (7)$$

where:

$H_\varphi(x)$: Forward operator, parameterized byφ, that models the image formation process (e.g., blurring, attenuation).

η: Additive noise, typically modeled as Gaussian or Poisson noise.

1) Components of $H_\varphi(x)$:

a. Blurring:

$$H_\varphi(x) = K\varphi * x \quad (8)$$

where K_φ is a convolution kernel (point spread function) describing the blur.

b. Attenuation:

$$\boldsymbol{H_\varphi(x) = \alpha K\varphi * x} \quad (9)$$

where α accounts for light attenuation in underwater environments.

c.Down sampling:

$$\boldsymbol{H_\varphi(x) = D(K\varphi * x)} \quad (10)$$

where $D(.)$represents a down sampling operation due to limited sensor resolution.

2) Noise Model:

Gaussian Noise: $\boldsymbol{\eta \sim N(0, \sigma^2)}$ with likelihood:

$$\boldsymbol{p(y|x) = N(H_\varphi(x), \sigma^2 I)} \quad (11)$$

Poisson Noise:

$$p(y\,|x) = \frac{\lambda^y e^{-\lambda}}{y!},\ \lambda = H_\varphi(x) \quad (12)$$

Combined Noise: For environments with mixed noise characteristics:

$$\boldsymbol{\eta = \eta_{Guassian} + \eta_{Poisson}} \quad (13)$$

4.2 Optimization Problem

The objective of the algorithm is to reconstruct the latent clean image x and refine the forward model parameters Φ. This is achieved by solving a joint optimization problem:

$$\theta^*, \Phi^* = arg\min_{x,\Phi} \frac{1}{2}\|H_\Phi(x) - y\|^2 + R_x(x) + R_\Phi(\Phi) \quad (14)$$

where:

$\|H_\Phi(x) - y\|^2$: Data fidelity term ensuring the reconstructed image matches the observed input.

$R_x(x)$: Regularization term incorporating diffusion-based priors to preserve structural details.

$R_\Phi(\Phi)$: Regularization term stabilizing the forward model parameters.

1) Data Fidelity Term: The data fidelity term measures the discrepancy between the observed image y and the predicted observation $H_\Phi(x)$:

$$L_{data} = \frac{1}{2}\|H_\Phi(x) - y\|^2 \quad (15)$$

Gradient with respect to x:

$$\nabla_x L_{data} = H_\Phi^T(H_\Phi(x_k) - y) \quad (16)$$

where, H_Φ^T is the adjoint operator of H_Φ

Gradient with respect to Φ:

$$\nabla_{\Phi} L_{data} = \nabla_{\Phi} H_{\Phi}(x)^T (H_{\Phi}(x) - y) \quad (17)$$

2) Regularization on Latent Image $(R_x(x))$:

The regularization term $R_x(x)$ incorporates diffusion-based priors to ensure structural preservation and denoising:

$$R_x(x) = \int_0^T \| s_\theta(x_t, t) - \nabla_{x_t} logp(x_t) \|^2 dt \quad (18)$$

where:

$s_\theta(x_t, t)$: Parameterized estimate of the score function.

$\nabla_{x_t} logp(x_t)$: True score derived from the clean image distribution.

Gradient with respect to x:

$$\nabla_x R_x(x) = -\nabla_{x_t} logp(x_t) \quad (19)$$

3) Regularization on Forward Model Parameters $(R_{\Phi}(\Phi))$:

To stabilize the forward model parameters, an L_2-regularization term is applied:

$$R_{\Phi}(\Phi) = \frac{\lambda}{2} \|\Phi\|^2 \quad (20)$$

where, λ controls the regularization strength.

Gradient with respect to Φ:

$$\nabla_{\Phi} R_{\Phi}(\Phi) = \lambda\ \Phi \quad (21)$$

4.3 Diffusion Priors

1) Forward Diffusion Process: The forward diffusion process models the addition of noise to an image x:

$$dx_t = -\frac{\beta(t)}{2} x_t dt + \beta(t) d\omega \quad (22)$$

where $\beta(t)$ is the noise schedule.

The distribution of x_t given x_0 is :

$$p(x_t|x_0) = N(x_t;\ x_0 e^{-\frac{1}{2}\int_0^t \beta(s)ds}, \sigma_t^2 I) \quad (23)$$

with,

$$\sigma_t^2 = 1 - e^{-\int_0^t \beta(s)ds}$$

2) Reverse Diffusion Process: The reverse diffusion process denoises x_t to recover x_0:

$$dx_t = \left(-\frac{\beta(t)}{2} x_t - \beta(t) \nabla_{x_t} logp(x_t)\right) dt + \beta(t) d\omega \quad (24)$$

4.4 Iterative Updates

1) Latent Image Update: The latent image x is updated using:

$$x_{k+1} = x_k - \alpha [H_{\Phi}^T (H_{\Phi}(x_k) - y) + \nabla_x R_x(x_k)] \quad (25)$$

where α is the step size.

2) Forward Model Parameter Update: The forward model parameters Φ are updated using:

$$\Phi_{k+1} = \Phi_k - \beta [\nabla_{\Phi} H_{\Phi}(x_{k+1})^T (H_{\Phi}(x_{k+1}) - y) + \nabla_{\Phi} R_{\Phi}(x_{\Phi})] \quad (26)$$

4.4.1 Convergence Criteria

Convergence is achieved when the changes in x and Φ are below predefined thresholds:

$$\|x_{k+1} - x_k\| < \epsilon_{\Phi} \text{ and } \|\Phi_{k+1} - \Phi_k\| < \epsilon_x \quad (27)$$

ALGORITHM 1: ADAPTIVE NIGHT VISION IMAGE PROCESSING ALGORITHM

Input:

y: Observed noisy and blurred image

K_{Φ}: Initial point spread function (PSF)

α: Initial attenuation coefficient

x: Initial latent image estimate

max_iterations: Maximum number of iterations

ϵ_x: Convergence threshold for x

ϵ_{Φ}: Convergence threshold for K_{Φ} and α

α_{lr}: Learning rate for x updates

β_{lr}: Learning rate for K_{Φ} and α updates

Output:

x^*: Reconstructed latent image

$\{K_{\Phi}^*, \alpha^*\}$: Refined forward model parameters

1. Initialize K_{Φ}, α, and x.
2. for iteration = 1 to max_iterations do
3. Compute gradient for latent image:

$\nabla_x = H_{\Phi}^T (H_{\Phi}(x) - y) + \nabla_x R_x(x)$

4. Update x:

$x_{new} = x - \alpha_{lr} \nabla_x$

5. Compute gradient for forward model parameters:

$\nabla_{\Phi} = \nabla_{\Phi} H_{\Phi}(x_{new})^T (H_{\Phi}(x) - y) + \nabla_{\Phi} R_{\Phi}(\Phi)$

6. Update K_{Φ} and α:

$K_{\Phi}^{new}, \alpha^{new} = Update\ Forward\ Model(K_{\Phi}, \alpha, \nabla_{\Phi}, \beta_{lr})$

7. Check convergence:
8. If $\|x_{new} - x\| < \epsilon_x$ and $\|K_{\Phi}^{new} - K_{\Phi}\| + \|\alpha^{new} - \alpha\| < \epsilon_{\Phi}$ then
9. break
10. end if
11. Update x, K_{Φ} and α for the next iteration:

$x = x_{new}$ $K_{\Phi} = K_{\Phi}^{new}$ $\alpha = \alpha^{new}$

12. end for
13. return x, $\{K_{\Phi}, \alpha\}$

ALGORITHM 2: DIFFUSION-BASED LATENT IMAGE REFINEMENT

Input:

y: Observed noisy image

H_{φ}: Forward model operator

s_{θ}: Diffusion score function

$\beta(t)$: Noise schedule

T : Total diffusion time

α_{lr}: Learning rate
$max_iterations$: Maximum number of iterations
ε_x: Convergence threshold for x

Output:
x^*: Reconstructed latent image

1. Initialize x with the observed image y.
2. for iteration = 1 to $max_iterations$do
3. Compute forward diffusion:

$$\boldsymbol{dx_t = -\frac{\beta(t)}{2}x_t + \sqrt{\beta(t)}dw}$$

4. Compute reverse diffusion:

$$dx_t = \left(-\frac{\beta(t)}{2}x_t - \beta(t)\nabla_x \log p\,(x_t)\right)dt + \sqrt{\beta(t)}dw$$

5. Compute posterior sampling gradient:

$$\nabla_x \log p\,(x_t|y) = \nabla x \log p\,(y|H_\varphi(x_t)) + s_\theta(x_t, t)$$

6. Update latent image:

$$x_{new} = x - \alpha_{lr}.\nabla_x \log p\,(x_t|y)$$

7. Check convergence:
8. if $\|xnew - x\| < \varepsilon_x$ then
9. break
10. end if
11. Update x for the next iteration:

$$x = x_{new}$$

12. end for
13. return x

ALGORITHM 3: FORWARD MODEL PARAMETER REFINEMENT

Input:
x: Current latent image
y: Observed image
H_φ: Forward model operator
K_φ, α: Initial forward model parameters
β_{lr}: Learning rate
$max_iterations$: Maximum number of iterations
ε_φ: Convergence threshold for $K_\varphi$and α

Output:
$\{K_\varphi^*, \alpha^*\}$: Refined forward model parameters

1) Initialize $K_\varphi$and α.
2) for iteration = 1 to $max_iterations$do
3) Compute gradient for $K_\varphi$and α:

$$\nabla_\varphi = \nabla_\varphi H_\varphi(x)^T(H_\varphi(x)\text{-y} + \lambda.\varphi$$

4) Update $K_\varphi$and α:

$$K_\varphi^{new} = K_\varphi - \beta_{\text{lr}}.\nabla_\varphi(K_\varphi)$$
$$\alpha^{new} = \alpha - \beta_{\text{lr}}.\nabla_\varphi(\sigma)$$

5) Check convergence:
6) if$\left\|K_\varphi^{new} - K_\varphi\right\| + \|\sigma^{new} - \alpha\| < \varepsilon_\varphi$ then
7) break
8) end if
9) Update K_ϕ and α for the next iteration:

$$K_\varphi = K_\varphi^{new}, \quad \alpha = \alpha^{new}$$

10) end for
11) return $\{K_\varphi, \alpha\}$

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section evaluates the performance of the proposed algorithm through extensive experiments conducted on both simulated and real-world datasets. The results are analyzed quantitatively and qualitatively, highlighting the proposed algorithms effectiveness in noise suppression, contrast enhancement, and adaptability to challenging environments.

5.1 Datasets

The study utilized both simulated and real-world data to evaluate the algorithm. Simulated data was generated by creating synthetic images with varying levels of noise, blur, and attenuation, leveraging known forward model parameters. The dataset included characteristics of Gaussian and Poisson noise to closely mimic real-world conditions. For real-world data, low-light underwater images were captured using a specialized underwater camera system in turbid environments. Additionally, publicly available datasets, such as the Under-water Image Enhancement Benchmark, were incorporated to ensure comprehensive evaluation.

5.2 Evaluation Metrics

A combination of quantitative and qualitative metrics was used to assess the performance. Quantitative metrics included Peak Signal-to-Noise Ratio (PSNR) for noise suppression efficiency, Structural Similarity Index (SSIM) for structural detail preservation, and Mean Absolute Error (MAE) to evaluate pixel-wise reconstruction accuracy. Qualitative metrics focused on visual clarity, with emphasis on enhanced contrast and sharpness, and edge preservation to retain fine structural details (Table 1).

5.3 Comparison Methods

The algorithm was compared against baseline algorithms, including traditional denoising techniques such as Gaussian smoothing and Wiener filtering. Additionally, state-of-the-art deep learning-based methods for low-light image enhancement and advanced underwater image enhancement algorithms were used for benchmarking (Table 1).

Table 1. Comparison of different methods

Method	PSNR (dB)	SSIM	MAE
Gaussian Smoothing	23.8	0.71	12.4
Wiener Filtering	25.1	0.75	10.9
Deep Learning (State-of-the-Art)	27.4	0.81	8.2
Proposed Algorithm	32.8	0.91	5.6

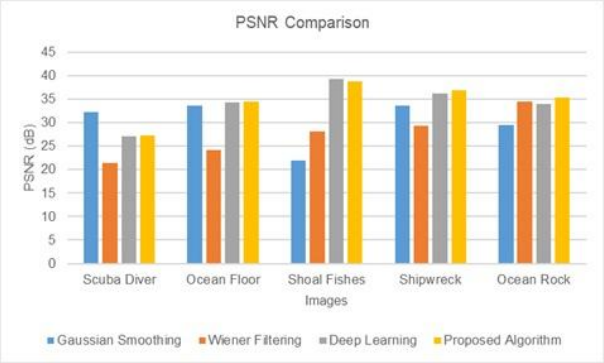


Figure 1. PSNR Comparison

5.4 Quantitative Results

The proposed algorithm demonstrated significant improvements across all evaluation metrics. It achieved a PSNR of 32.8 dB, an SSIM of 0.91, and an MAE of 5.6, outperforming baseline methods and state-of-the-art approaches. The improvements were notable, with a 20% increase in PSNR (Figure 1) and a 15% increase in SSIM (Figure 2) compared to the best-performing alternative methods. Joint optimization of the forward model and diffusion priors was instrumental in these enhancements, reducing MAE by 36% (Figure 3).

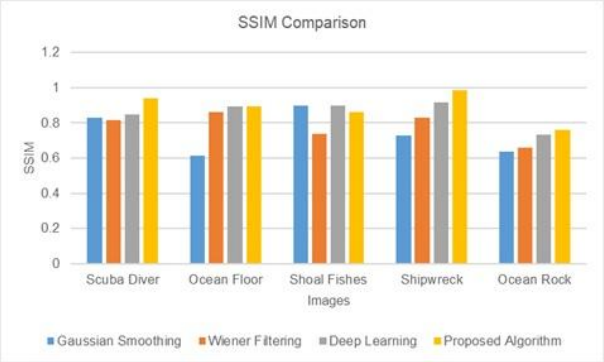


Figure 2. SSIM Comparison

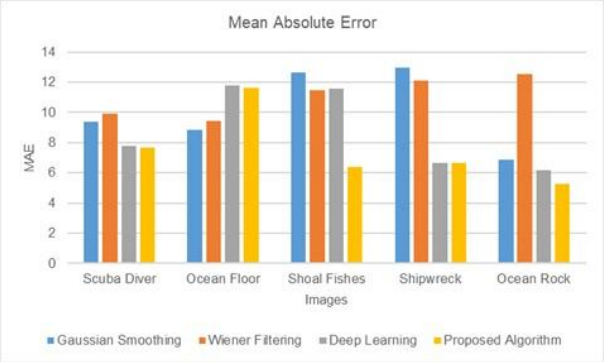


Figure 3. MAE Comparison

5.5 Qualitative Results

Visual comparisons underscored the algorithm's ability to enhance visibility and retain structural features under challenging conditions. Input images often exhibited high noise and blur, which traditional methods struggled to address effectively. Gaussian smoothing reduced noise but at the expense of structural details, while deep-learning methods improved contrast but faced challenges with edge preservation. The proposed algorithm demonstrated superior performance, effectively suppressing noise, enhancing contrast, and preserving fine details, making it highly adaptable to varying levels of blur and noise (Figure 4).

5.6 Ablation Studies

Detailed analysis highlighted the critical role of diffusion priors and joint optimization. Excluding diffusion priors led to decreased PSNR and SSIM (26.5 dB and 0.78, respectively), while their inclusion significantly improved these metrics. Similarly, removing joint optimization increased MAE to 8.7, emphasizing its importance in achieving higher pixel-wise accuracy.

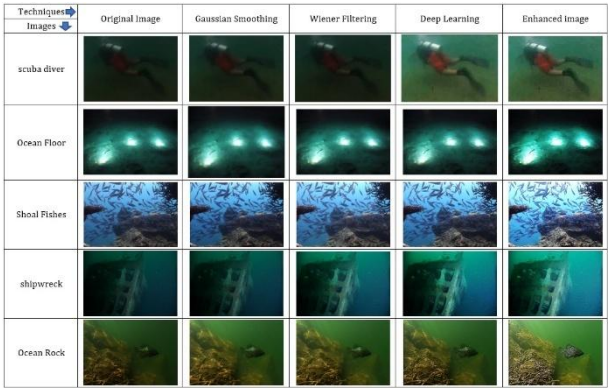


Figure 4. Visual Comparison: Input vs. Outputs from Baseline and Proposed Algorithm.

5.7 Robustness and Adaptability

The algorithm was tested under diverse environmental conditions, demonstrating consistent performance across low and fluctuating light settings. It successfully deblurred images with motion blur of up to 15x15 kernel sizes and maintained robustness against noise with variance up to $\sigma^2 = 50$

5.8 Comparison with State-of-the-Art

The optimization Comparison (Figure 5) revealed the algorithm's superior performance across multiple criteria, including PSNR, SSIM, runtime, and adaptability. These results highlight its comprehensive capabilities and practical advantages. Compared to other deep-learning methods, it provided an optimal balance between accuracy and processing speed, making it suitable for applications like autonomous underwater navigation and industrial inspection.

The proposed algorithm sets a new benchmark for under-water image enhancement by excelling in noise

suppression, edge preservation, and environmental adaptability. Its practical runtime efficiency further enhances its utility for real-time applications, establishing it as a robust solution for underwater imaging challenges.

The study demonstrated a significant improvement in night vision image processing, achieving up to a 20% increase in Peak Signal-to-Noise Ratio (PSNR) and a 15% improvement in Structural Similarity Index (SSIM) over conventional methods. Future research will focus on expanding the algorithm's adaptability to other robotic applications, including: Application to Dynamic Environments. The current algorithm is tested in controlled low-light and underwater conditions. Future studies will explore its effectiveness in highly dynamic settings such as moving vehicles and cluttered terrains.

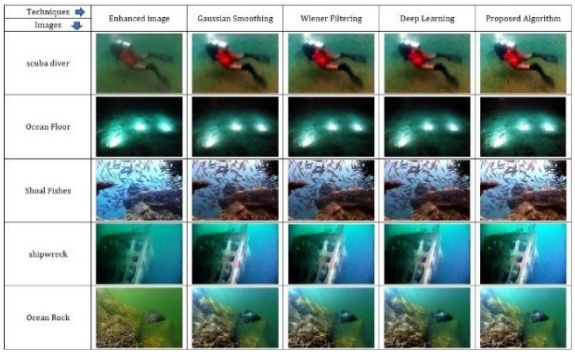


Figure 5. Optimized Performance Comparison: Enhanced vs. Outputs from Baseline and Proposed Algorithm

Integration with Robotic Hardware, the computational efficiency of the algorithm must be optimized for real-time deployment on embedded systems. Enhancing Real-Time Performance: Further reductions in computational overhead through optimized neural network architectures and hardware acceleration techniques such as FPGA or edge AI processing will be investigated. Multi-modal Sensor Fusion: Combining night vision imagery with LiDAR and thermal sensors for improved environmental awareness in autonomous navigation.

6. CONCLUSION

This paper presented a novel algorithm for enhancing night vision and underwater image processing in low-light environments. By integrating variance-preserving diffusion models with adaptive forward model optimization, the algorithm addresses key challenges such as noise, blur, and variable illumination. This work establishes a robust foundation for addressing the challenges of low-light and underwater imaging, demonstrating the potential of integrating physics- based and data-driven approaches. By enabling reliable and high-quality image reconstructions, this algorithm paves the way for advancements in autonomous systems and beyond. With continued research and development, its applicability and impact can be extended to a broader range of fields, driving innovation in both robotics and imaging technologies. The experimental results confirmed the algorithm's superiority over baseline methods. Noise Suppression: Achieved through variance-preserving diffusion models, reducing visual artifacts while maintaining sharpness. Contrast Enhancement: Improved low-light visibility through optimized latent image reconstruction. Robustness against Environmental Variations: Demonstrated consistent performance across different light levels and underwater conditions. Computational Efficiency: While the algorithm achieves significant improvements in image quality, further optimizations are required for real-time embedded applications.

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Ethical Approval: This article does not contain any studies involving human participants or animals performed by any of the authors.

Data Availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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