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AURIE-Net: Adaptive Retinex-Based Framework for Underwater Image Restoration

Palem Narasimhulu[1*], Vishnu Soni[2], Shivam Yadav[3]
[1]Research Scholar, APEX University, Jaipur-303002, Rajasthan, India
[2]Assistant Professor, APEX University, Jaipur-303002, Rajasthan, India
[3]Research Scholar, APEX University, Jaipur-303002, Rajasthan, India

CORRESPONDING AUTHOR

Palem Narasimhulu
e-mail: pnarasimha.p@gmail.com

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Abstract

Underwater image enhancement is a vital task in computer vision due to severe image degradation caused by wavelength-dependent light absorption and scattering in aquatic environments. This paper presents a novel enhancement framework, AURIE (Adaptive Underwater Retinex Image Enhancement), which integrates Retinex theory with adaptive color correction and frequency-based decomposition for robust underwater image restoration. The proposed method decomposes the input into low- and high-frequency components, enabling illumination correction in the HSI color space and detail refinement via edge-preserving filters. A customized RetinexNet is introduced to perform gamma-based illumination adjustment and feature-preserving reflectance enhancement using attention-guided refinement. The network is optimized using perceptual, structural, and color consistency losses. Extensive experiments on benchmark datasets (UIEB, EUVP) demonstrate superior performance in UCIQE, UIQM, PSNR, and SSIM compared to existing techniques. The architecture is also lightweight and computationally optimized, making it suitable for real-time deployment in autonomous underwater systems for applications in marine exploration and underwater robotics.

1. Introduction

Underwater image processing is crucial for applications such as marine research, exploration, and surveillance; however, conventional enhancement methods often fall short due to underwater-specific challenges like color distortion, blurriness, and low contrast caused by light absorption and scattering. These distortions significantly reduce the quality of underwater images, which are further affected by the physical properties of the water medium, such as light attenuation and scattering. To overcome these limitations, this study proposes a deep learning-based enhancement model that integrates traditional color correction with a semantically guided Generative Adversarial Network (GAN), operating in the LAB color space to specifically enhance the luminance channel for better brightness and detail retention. Underwater image enhancement is vital for applications such as marine research, ocean exploration, and autonomous underwater navigation. However, challenges like wavelength-dependent light absorption, scattering, low visibility, strong color casts, and reduced contrast degrade image quality in aquatic environments. Traditional methods often fall short, as they cannot adapt to the spatially and depth-dependent nature of underwater distortions.

Fig.1 Example of Underwater Image degradation due to scattering and absorption

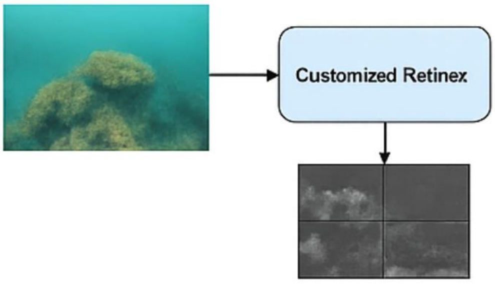


Fig.2 Frequency decomposition into low- and high-frequency components

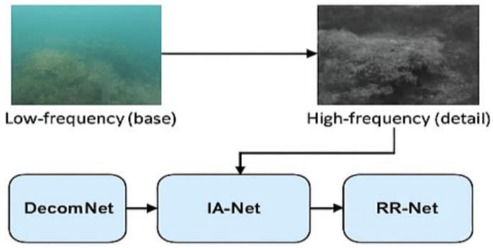


Fig.3 Customized RetinesNet architecture for underwater enhancement

Fig.4 Real-time AURIE enhancement pipeline application in AUVs

This paper presents AURIE (Adaptive Underwater Retinex Image Enhancement)—a modular enhancement framework that combines Retinex theory with frequency-based image decomposition. The input image is split into low- and high-frequency components, which are independently enhanced: the low-frequency layer is corrected in HSI color space to address illumination and color imbalance, while the high-frequency layer undergoes edge-preserving filtering to recover detail. The Figure 2 illustrates this decomposition.
AURIE also integrates a deep-learning-based Customized RetinexNet, which includes modules for learned decomposition, gamma correction, and detail refinement using attention and dilated convolutions as showed in the Figure 3. This hybrid approach merges the interpretability of traditional processing with the adaptability of neural networks. The complete AURIE pipeline supports real-time enhancement for underwater systems for the figure 4, such as AUVs and camera platforms, enabling clearer visuals for downstream vision tasks.

2. Related Work

In recent years, underwater vision has gained significant attention due to its wide range of applications, making underwater image enhancement (UIE) both an important and challenging task. This difficulty arises from complex underwater imaging conditions and the limitations of capture devices. Enhancement techniques are generally divided into non-deep learning (non-DL) and deep learning (DL) methods. While non-DL approaches are simpler and computationally less demanding, they often result in poor visual outcomes and lack robustness. In contrast, DL methods, although computationally intensive, offer better generalization and adaptability by learning patterns directly from data.

Underwater image enhancement has progressed considerably in recent years, moving from conventional image processing techniques to more sophisticated deep-learning-based methods. Traditional approaches, such as histogram equalization, white balancing, and Contrast-Limited Adaptive Histogram Equalization (CLAHE), offer computational efficiency and simplicity but fall short in addressing complex degradations inherent to underwater environments. These methods operate on global statistics and fail to consider the spatially varying nature of underwater distortions.
To overcome these limitations, Retinex-based techniques were introduced, including Single-Scale Retinex (SSR) and Multi-Scale Retinex with Color Restoration (MSRCR). These methods simulate the human visual system by separating the image into reflectance and illumination components, allowing better contrast and color correction. However, they are often sensitive to noise and lack adaptability due to fixed parameter settings. (Figure 5, left) illustrates an example of enhancement using MSRCR, where results show modest improvement but remain susceptible to detail loss and over-saturation.

Fig.5 Comparative outputs – MSCRR (Left), Water-Net (Middle), AURIE (Right)

With the emergence of deep learning, models such as UGAN, Water-Net, and Sea-Thru have shown promising results. These methods employ convolutional neural networks (CNNs) and generative adversarial frameworks to learn end-to-end enhancement mappings. While these approaches can produce visually compelling outputs and improve generalization, they typically require large-scale annotated datasets and are computationally intensive. (Figure 5, center) depicts enhanced results from a learning-based method (e.g., Water-Net), offering better contrast and detail retention than classical methods.
AURIE bridges the gap between these paradigms by combining the physics-driven structure of Retinex theory with the flexibility and adaptability of modern neural networks. It integrates handcrafted frequency-based decomposition with a trainable RetinexNet, enabling both interpretability and data-driven optimization. This hybrid approach allows AURIE to perform competitively with deep-learning models while maintaining real-time efficiency. (Figure 5, right) shows the enhanced image output from AURIE, balancing color fidelity, edge preservation, and overall visibility.

3. Proposed Methodology

AURIE is composed of a hybrid enhancement pipeline that strategically combines handcrafted image processing techniques with data-driven deep learning modules. This integration allows AURIE to leverage the strengths of traditional models—such as physical interpretability, controllability, and low computational cost—while also benefiting from the adaptability and feature abstraction capabilities of neural networks. The handcrafted components, rooted in Retinex theory and frequency decomposition, enable precise control over illumination and texture enhancement, whereas the learned components, implemented via the Customized RetinexNet, allow the system to adaptively refine outputs based on context and scene content. This dual design ensures AURIE maintains high enhancement performance across diverse underwater conditions while remaining interpretable and suitable for real-time applications.

3.1 Data Preparation

To ensure robustness and generalization, the AURIE model is trained and evaluated using a comprehensive dataset composed of both real-world underwater images and synthetically generated samples. This dual-sourcing strategy enhances the diversity of training conditions, allowing the model to perform reliably across a broad spectrum of underwater environments.

- **Public Datasets (UIEB, EUVP):** These benchmark datasets include a wide range of underwater imagery captured in real-world scenarios. The images span various conditions—different water types (clear, turbid), depths, illumination patterns, and scene content (reefs, open water, marine organisms). Such diversity ensures that the model encounters a variety of visual distortions during training, such as color casts, haze, and low contrast.
- **Synthetic Data Generation:** To supplement real-world data, synthetic underwater images are generated using physics-based models that simulate light attenuation and scattering based on depth, turbidity, and wavelength absorption properties. This enables the creation of controlled scenarios with tunable degradation levels, which are particularly useful for training the model on edge cases and underrepresented conditions.

For supervised training, ground truth images are either obtained from available clear-reference images or approximated using multi-image fusion techniques, where multiple degraded inputs are algorithmically combined to infer a visually plausible undistorted reference. The final dataset is partitioned into training, validation, and testing subsets to facilitate proper learning, hyper-parameter tuning, and performance evaluation.

3.2 Frequency Decomposition

To enable adaptive and targeted enhancement, the input RGB image is decomposed into low-frequency and high-frequency components via low-pass filtering (e.g., Gaussian or bilateral filter). This decouples global illumination and color trends from fine-grained structural content.

- **Low-Frequency Component (L):** Encodes broad-scale information such as luminance gradients, color cast, and overall scene brightness—key aspects affected by underwater light attenuation and scattering.
- **High-Frequency Component (H):** Captures texture, fine edges, and detailed scene structures that are often degraded or blurred in underwater conditions.

This decomposition supports AURIE’s dual-path processing: one path focuses on global perceptual corrections (illumination, chromaticity), while the other emphasizes localized structural fidelity.

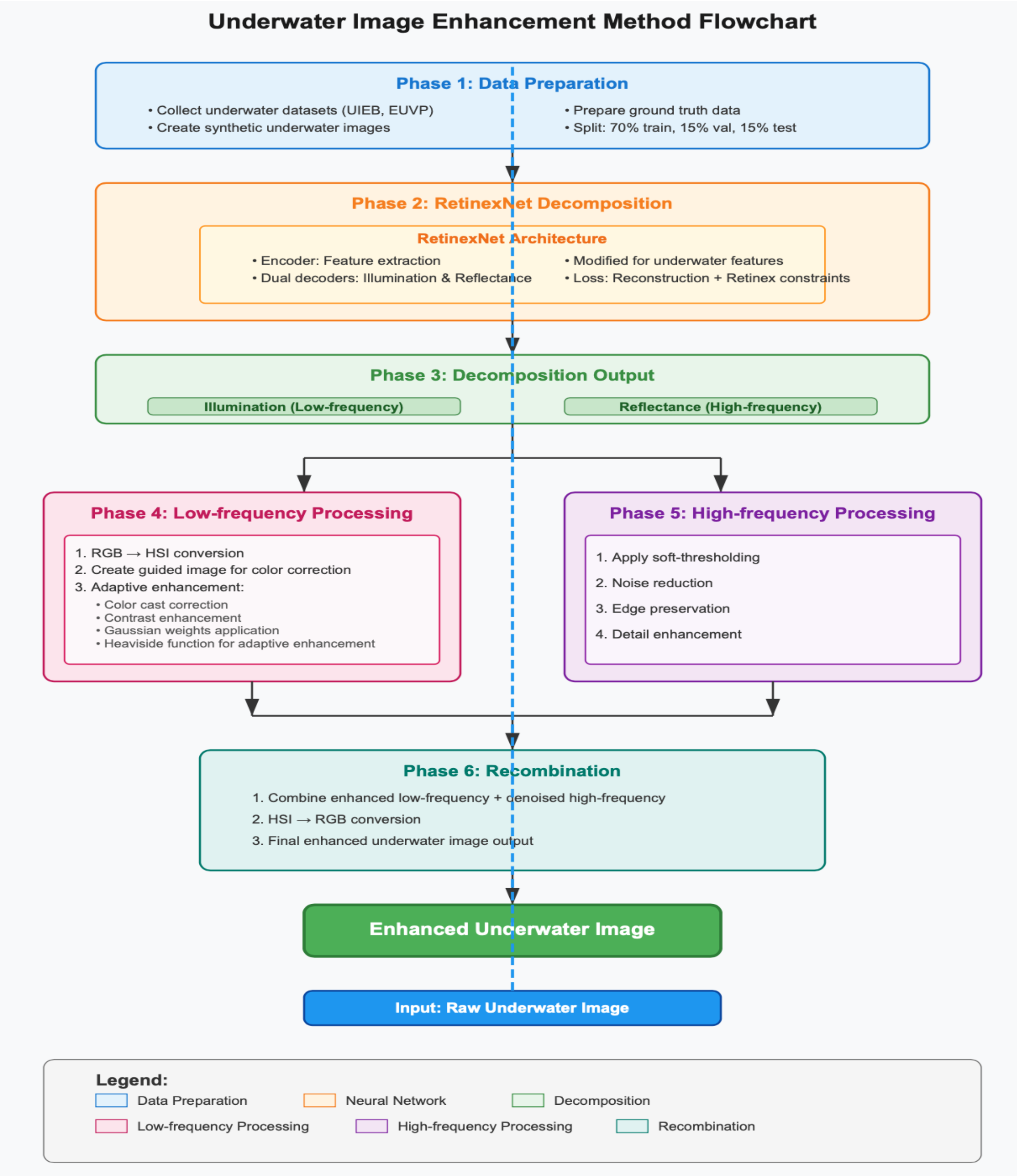
3.3 Low-Frequency Enhancement

The low-frequency component is processed in the HSI color space to exploit its perceptual alignment with human vision and its ability to separately manipulate brightness and chroma

Color Cast Correction: Adjustments to hue and saturation components mitigate bluish/greenish color shifts by rebalancing chromatic information based on underwater color priors.

Adaptive Contrast Enhancement: The intensity channel is enhanced using Gaussian-weighted smoothing for brightness balancing and Heaviside step functions to non-linearly amplify low-illumination zones, improving contrast without overexposing highlights.

Recomposition Prep: The enhanced L component is normalized and prepared for fusion with the refined high-frequency details, ensuring structural consistency and tonal continuity in the final image.



3.4 High-Frequency Enhancement

The high-frequency map is prone to noise and compression artifacts. Two methods are used:

- **Guided Filtering:** Smooths textures using the base layer as reference.
- **Bilateral Filtering:** Retains edge integrity while reducing noise.

3.5 Final Image Reconstruction

The final stage in the AURIE pipeline involves fusing the independently enhanced low-frequency and high-frequency components to reconstruct a visually coherent RGB image. This fusion is essential for restoring both global luminance and local texture details, resulting in an image that is perceptually balanced and visually appealing. We are considered two primary fusion strategies:

- **Multiplicative Fusion:** The reflectance and illumination components are multiplied pixel-wise to mimic the physical interaction of light and surface reflection, consistent with Retinex theory. This

method enhances natural brightness and shadow effects but may intensify noise if not properly constrained.
- **Additive Fusion:** High-frequency details are added back to the base (low-frequency) layer after enhancement. This approach provides more control over contrast and sharpness, particularly effective when detail preservation is prioritized.

In AURIE, an adaptive mechanism selects the optimal fusion method based on local image properties such as gradient strength, illumination uniformity, and entropy. This ensures that the final output maintains a high level of color fidelity, structural integrity, and perceptual clarity.

Fig.6 Final image reconstruction through fusion of low and high frequency components

The figure 6, demonstrates the reconstruction process, where the separately processed components are seamlessly combined into a final, high-quality underwater image.

4. Experimental Results

The experimental workflow depicted in the figure demonstrates the end-to-end architecture of the AURIE framework, beginning with deep Retinex-based decomposition of the input underwater image. This process uses a series of convolutional layers to separate the image into two distinct components: reflectance and illumination. The reflectance map retains essential scene textures and color details, while the illumination map captures the spatial distribution of lighting. This separation allows for precise, component-specific enhancement, tailored to the unique degradation patterns found in underwater imagery.

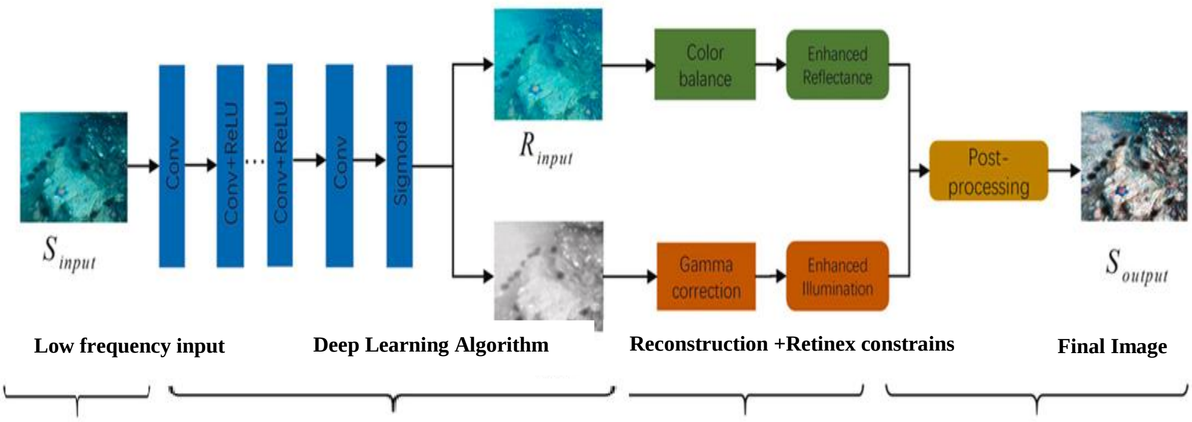


Figure 7. Practical implementation of Depp learning with image reconstruction through fusion of low and high frequency components

4.1 Datasets and Baselines

AURIE is evaluated using two benchmark datasets: UIEB (Underwater Image Enhancement Benchmark) and EUVP (Enhancement of Underwater Visual Perception). These datasets encompass a wide variety of underwater scenarios, including shallow reef scenes, deep-sea environments, and synthetic degradations. For comparative analysis, AURIE is benchmarked against well-known enhancement methods: MSRCR (a classical Retinex-based model), CLAHE (a global contrast adjustment method), UGAN (a generative adversarial network-based method), and Water-Net (a learning-based model using scene depth and light modelling).

4.2 Evaluation Metrics

To assess the performance of AURIE in both perceptual and quantitative terms, the following metrics are utilized:

- **UCIQE (Underwater Color Image Quality Evaluation):** Focuses on evaluating image contrast, chroma, and saturation.
- **UIQM (Underwater Image Quality Measure):** Assesses image sharpness, colorfulness, and contrast.
- **PSNR (Peak Signal-to-Noise Ratio):** Measures the fidelity of the reconstructed image compared to the ground truth.
- **SSIM (Structural Similarity Index):** Evaluates the structural consistency between the enhanced and reference images.

These metrics collectively offer a comprehensive analysis of enhancement effectiveness from low-level accuracy to high-level visual quality.

4.3 Qualitative and Quantitative Analysis

AURIE demonstrates significant improvements over baseline methods:

- Enhanced perceptual quality with natural color reproduction and balanced tonal correction.
- Superior edge preservation and reduction in haze, contributing to sharper visual features.
- Consistently high scores across UCIQE, UIQM, PSNR, and SSIM, validating the framework's strength in both detail enhancement and visual realism.

Sample enhanced images reveal that AURIE avoids common artifacts like overexposure, unnatural tints, and loss of texture, which frequently appear in classical or over-optimized neural methods.

5. Conclusion

This paper presented AURIE, an adaptive underwater image enhancement framework that integrates Retinex theory, frequency decomposition, and deep-learning-based feature refinement. AURIE effectively addresses key underwater image degradation issues such as color cast, low contrast, and loss of clarity. It achieves perceptual and quantitative superiority over existing methods and maintains computational feasibility for real-time applications. AURIE’s hybrid nature makes it a compelling candidate for deployment in practical underwater imaging systems.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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