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Mathematical Modelling and Computational Approach for Underwater Image Enhancement Using Dark Channel Prior and Filtering Techniques

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Abstract
Underwater imagery is a critical tool for marine exploration, infrastructure inspection, and biological research. However, the aquatic medium severely degrades image quality through wavelength-dependent light absorption and scattering, leading to pervasive color casts, diminished contrast, and loss of detail. This paper presents a robust computational framework for underwater image enhancement by integrating the Dark Channel Prior (DCP), originally developed for haze removal in atmospheric environments, with advanced filtering techniques. The proposed model first employs the DCP to estimate the depth map and the global background light, effectively characterizing the veiling effect. A transmission map is subsequently refined using a guided filter to suppress noise and block artifacts while preserving edge information. The restored image is then reconstructed by inverting the underwater optical model. Furthermore, a post-enhancement white balancing and contrast stretching module is incorporated to rectify residual color inaccuracies and improve dynamic range. Experimental results on a diverse dataset of underwater scenes demonstrate that the proposed method achieves superior performance in color fidelity, contrast enhancement, and edge clarity compared to several state-of-the-art techniques, providing a more reliable computational solution for autonomous underwater vehicles and marine scientific analysis.

Keywords: Underwater Image Enhancement, Dark Channel Prior, Computational Imaging, Guided Filtering, Image Restoration, Haze Removal.

1. Introduction

The exploration and monitoring of the underwater realm are of paramount importance to a diverse array of scientific, commercial, and environmental endeavors. Applications spanning marine biology, offshore infrastructure inspection, archaeological discovery, and defense operations rely heavily on high-quality visual data acquired through remotely operated vehicles (ROVs) and autonomous underwater vehicles (AUVs). However, the aquatic environment presents a formidable challenge to optical imaging, fundamentally limiting the clarity and utility of captured imagery. The primary degradations stem from the physical properties of water itself, where light undergoes wavelength-dependent absorption and scattering. Absorption selectively diminishes light intensity over distance, with longer wavelengths (reds) being absorbed first, resulting in the characteristic blue-green color cast prevalent in most underwater photographs. Simultaneously, scattering occurs as light particles are deflected by suspended particulates and plankton, leading to a hazy, low-contrast appearance and a loss of fine detail. This dual phenomenon of absorption and scattering, often modeled as an additive veil of "backscatter" and a signal-attenuating "forward scatter," significantly obscures visual information, thereby impeding the performance of both human analysis and automated computer vision systems such as object detection, segmentation, and classification.

The scope of this research is situated within the domain of computational photography and digital image processing, specifically targeting the enhancement of single, static underwater images without requiring specialized hardware or multiple captures. While numerous approaches have been proposed, they can be broadly categorized into image enhancement techniques, which operate directly on the pixel values to improve contrast and color (e.g., histogram equalization, Retinex theory), and image restoration techniques, which seek to invert a physical model of the degradation process. Enhancement methods, though often computationally efficient, can frequently introduce unrealistic colors and amplify noise. Restoration methods, while more physically grounded, are critically dependent on the accurate estimation of scene parameters, such as the depth-dependent transmission map and the global background light. It is within this context that the Dark Channel Prior (DCP), a powerful statistical observation from terrestrial haze removal, offers a compelling foundation. The DCP posits that in most non-sky patches of a haze-free outdoor image, at least one color channel has very low intensity for some pixels. This prior has proven remarkably effective in estimating the transmission of light through haze. However, its direct application to the underwater domain is non-trivial, as the dominant color cast and the unique spectral properties of water violate the standard DCP assumptions, often leading to an overestimation of haze and unnatural restoration outcomes.

The principal motivation for this work is to bridge the gap between the potent theoretical framework of the DCP and the specific exigencies of the underwater optical environment. We are driven by the need to develop a robust, computationally tractable model that not only mitigates the limitations of the standard DCP in water but also synergizes it with advanced filtering techniques to produce visually pleasing and quantitatively superior results. The core objectives of this paper are threefold: first, to adapt and refine the Dark Channel Prior for underwater scenes by integrating a color correction pre-processing step to counteract the severe spectral imbalance; second, to develop a robust transmission estimation and refinement pipeline utilizing a guided filter to smooth homogeneous regions while preserving critical edge information, thereby eliminating the block artifacts common in coarse DCP implementations; and third, to incorporate a post-restoration module for global contrast stretching and color fidelity enhancement, ensuring the final output is optimized for both human perception and subsequent machine vision tasks. The performance of the proposed model will be rigorously evaluated against contemporary state-of-the-art methods using a combination of full-reference and no-reference image quality metrics.

The remainder of this paper is systematically structured to elaborate on this proposed framework. Following this introduction, Section 2 provides a comprehensive review of the relevant literature on underwater image enhancement and restoration. Section 3 details the foundational background of the underwater image formation model and the Dark Channel Prior. Section 4 presents the complete methodology of our proposed integrated model, explaining each component in depth. Section 5 describes the experimental setup, presents the results of our comparative analysis, and provides a critical discussion of the findings. Finally, Section 6 concludes the paper by summarizing the key contributions and suggesting potential avenues for future research. This work aims to establish that a carefully calibrated integration of a physical prior with sophisticated computational filtering can significantly advance the state-of-the-art in autonomous underwater vision systems.

2. Literature Review

The challenge of underwater image enhancement has garnered significant attention within the computer vision and image processing communities, leading to a proliferation of methodologies that can be broadly classified into two paradigms: non-physical model-based enhancement techniques and physical model-based restoration techniques. Enhancement approaches operate directly on the image pixel values, aiming to improve perceptual quality without explicitly modeling the degradation process. Early and fundamental work in this category includes histogram equalization and its variants, which strive to redistribute pixel intensities to improve contrast. While computationally simple, these global methods often lead to over-enhancement and noise amplification in homogeneous regions [8]. To address these limitations, the Retinex theory, which models the human visual system's perception of color and lightness, has been widely adopted. Fu et al. [3] proposed a Retinex-based approach that decomposes an image into reflectance and illumination components, enhancing the structure and texture details. Similarly, Ancuti et al. [2] introduced a fusion framework that combines inputs from a white-balanced version and a contrast-enhanced version of the original image, effectively integrating complementary information to produce a robust result. While these methods can yield visually appealing outputs, they often lack a physical basis and may introduce unrealistic color artifacts, limiting their utility for scientific analysis.

In contrast, physical model-based restoration techniques seek to invert the degradation process by employing an optical model of the underwater environment. The most widely adopted model is derived from atmospheric scattering models, adapted for the underwater medium as follows: $I(x) = J(x)t(x) + B(1 - t(x))$, where $I(x)$ is the observed degraded image, $J(x)$ is the scene radiance (the ideal, clear image), $t(x)$ is the medium transmission map describing the portion of light that reaches the camera, and B is the global background light [10, 11]. The core challenge in this approach is the accurate estimation of the transmission map $t(x)$ and the background light B. A seminal breakthrough in this domain was the introduction of the Dark Channel Prior (DCP) by He et al. [10] for single image haze removal. The DCP is based on the statistical observation that in most non-sky patches of a haze-free outdoor image, at least one color channel has some pixels with very low intensity. This dark channel value is directly correlated with the haze thickness, enabling robust estimation of the transmission map. Drews et al. [11] were among the first to explore the application of DCP to underwater images, proposing an underwater DCP (UDCP) that operates only on the blue and green channels to account for the dominant red-light absorption. However, this adaptation, while insightful, often results in an overestimation of haze in regions with intrinsic dark objects, leading to color distortion.

The inherent limitations of the standard DCP in underwater settings have spurred numerous refinements. Peng et al. [7] proposed a generalized DCP that incorporates image blurriness and light absorption to improve transmission estimation. Other researchers have integrated DCP with complementary color correction strategies. For instance, Li et al. [9] proposed a color correction method based on weakly supervised color transfer to address color distortion. Galdran et al. [14] leveraged the red-channel deficiency for restoration, while Berman et al. [5] introduced a data-driven method based on 'haze-lines' to cluster pixels and estimate the transmission more accurately. A critical step in any DCP-based pipeline is the refinement of the initial, coarse transmission map. The conventional soft matting algorithm used in the original DCP is computationally intensive. To address this, He et al. [4] later introduced the guided filter, an edge-preserving smoothing filter that is orders of magnitude faster and highly effective for transmission map refinement, a technique that has been widely adopted in subsequent works, including [12].

More recently, the field has been revolutionized by data-driven deep learning approaches. These methods learn the complex mapping from degraded to enhanced images from large datasets. Wang et al. [13] developed a convolutional neural network (CNN) for end-to-end enhancement, while Li et al. [1] proposed WaterGAN, an unsupervised generative adversarial network to synthesize realistic underwater images from in-air imagery and depth information, thereby alleviating the data scarcity problem. Islam et al. [6] focused on perceptual enhancement for fast robotic applications. Deep learning models have demonstrated state-of-the-art performance; however, they are often criticized for their "black-box" nature, massive data requirements, and lack of generalizability to unseen environments. Furthermore, the model of Lu et al. [15] combines descattering with super-resolution, pushing the boundaries of recovering fine details. Despite their power, the performance of these deep learning models is intrinsically tied to the quality and diversity of their training data, and they can struggle with images that deviate significantly from the training distribution.

2.1 Research Gap

A comprehensive analysis of the existing literature reveals a distinct research gap. While physical model-based methods like DCP offer interpretability and do not require training data, their direct application to underwater scenes is hampered by the violation of the prior's assumptions, leading to color inaccuracies and block artifacts. On the other hand, deep learning methods, while powerful, lack transparency and are resource-intensive. There exists a critical need for a robust, computationally efficient, and physically-grounded model that specifically addresses the shortcomings of the DCP in the underwater context. Many existing DCP variants either fail to adequately handle the severe color cast or rely on complex, computationally expensive post-processing. Therefore, a significant opportunity lies in the development of an integrated computational framework that systematically combines a color-corrected DCP adaptation with an advanced, edge-preserving filtering technique for transmission refinement, followed by a dedicated post-processing module to ensure color fidelity and contrast. This work aims to fill this gap by proposing a holistic pipeline that leverages the strengths of the physical model while mitigating its weaknesses through targeted algorithmic interventions, offering a balanced solution between the interpretability of model-based approaches and the performance of data-driven methods

3. Mathematical Background and Underwater Image Formation Model

The foundation of any physics-based image restoration technique lies in the precise mathematical formulation of the degradation process. For underwater image enhancement, this involves modeling the interaction of light with the aquatic medium, which is fundamentally governed by the processes of absorption and scattering. The widely accepted model is an adaptation of the atmospheric scattering model, tailored to account for the spectral characteristics of water. This section delineates the core mathematical models that underpin the proposed enhancement framework, namely the Underwater Image Formation Model and the Dark Channel Prior.

3.1. The Underwater Optical Model

The degradation of an image captured in an underwater environment can be described by a simplified radiative transfer equation. The observed intensity, **I(x)**, at a pixel location **x** is a linear combination of two primary components: the direct signal and the backscattered signal. The direct signal constitutes the light that originates from the target object, **J(x)**, and reaches the camera after being attenuated by the water column. The backscattered signal, often referred to as the veiling light or airlight, is the ambient light scattered towards the camera by the water particles along the line of sight. This relationship is formally expressed as:

$$\mathbf{I(x) = J(x)t(x) + B_\infty(1 - t(x))} \quad (1)$$

In this equation:

- **I(x)**is the observed degraded image.
- **J(x)** is the scene radiance, which represents the ideal, haze-free image we aim to recover.
- **t(x)** is the medium transmission map, describing the fraction of the object's radiance that successfully reaches the camera without being scattered or absorbed. It is a function of the distance **d(x)** from the camera to the object and the total attenuation coefficient **c(λ)**, which is wavelength-dependent. The transmission is given by Beer-Lambert's law: $\mathbf{t(x) = e^{-c(\lambda) * d(x)}}$ (2)
- $\mathbf{B_\infty}$ is the global background light, often approximated as the intensity of the water body in regions at infinity, where no object information is present (e.g., the hazy background in the scene).

A critical distinction in underwater imaging, as opposed to atmospheric haze, is the strong wavelength-dependent attenuation. The attenuation coefficient **c(λ)** can be decomposed into the absorption coefficient **a(λ)** and the scattering coefficient **b(λ)**, i.e., **c(λ) = a(λ) + b(λ)**. In clear oceanic water, absorption is highest for longer wavelengths (red light) and lowest for shorter wavelengths (blue light). This differential attenuation is the primary cause of the pervasive blue-green color cast. To account for this, the optical model in Eq. (1) is often considered independently for each color channel, though a common transmission map **t(x)** is frequently assumed for computational simplicity, representing an average attenuation across channels.

3.2. The Dark Channel Prior (DCP)

The Dark Channel Prior, introduced by He et al. [10], is a powerful statistical observation from outdoor haze-free images. The dark channel, $\mathbf{J_{dark}(x)}$, for a haze-free image **J** is defined as the minimum intensity across the red, green, and blue channels within a local patch **Ω(x)** centered at pixel **x**:

$$\mathbf{J_{dark}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{r,g,b\}} J^c(y) \right)} \quad (3)$$

The core tenet of the DCP states that for most non-sky patches in a haze-free image, the value of $\mathbf{J_{dark}(x)}$ is very low and tends to zero, i.e.:

$$\mathbf{J_{dark}(x) \to 0} \quad (4)$$

This is because in a clear image, at least one color channel in a local patch will have some pixels that are very dark due to shadows, colored objects, or dark surfaces. In the presence of haze, the observed intensity **I(x)** is increased by the additive airlight component. The prior is applied to the haze formation model by taking the minimum operation on both sides of Eq. (1). Assuming the background light $\mathbf{B\infty}$ is known and the transmission $\mathbf{t(x)}$ is constant within the local patch $\mathbf{\Omega(x)}$, we can write:

$$\min_{y \in \Omega(x)} \left(\min_c I^c(y) \right) = t(x) \min_{y \in \Omega(x)} \left(\min_c J^c(y) \right) + (1 - t(x)) B\infty^c \quad (5)$$

Since $\mathbf{J}$ is a haze-free image, applying the dark channel prior from Eq. (4) implies that $\min_{y \in \Omega(x)} \left(\min_c J^c(y) \right) \approx 0$. Substituting this into Eq. (5) allows us to solve for the transmission map $\mathbf{t(x)}$:

$$\min_{y \in \Omega(x)} \left(\min_c I^c(y) \right) \approx (1 - t(x)) B\infty^c \quad (6)$$

Rearranging Eq. (6), we obtain an initial, coarse estimate of the transmission map:

$$\tilde{t}(x) = 1 - \omega * \min_{y \in \Omega(x)} \left(\min_c I^c(y) / B\infty^c \right) \quad (7)$$

Here, a constant parameter $\boldsymbol{\omega}$ $(0 < \omega \leq 1)$ is introduced as a fine-tuning parameter to retain a small amount of haze for distant objects, ensuring the result appears natural. Typically, $\boldsymbol{\omega}$ is set to a value such as 0.95. The background light $\mathbf{B\infty}$ is typically estimated by selecting the pixels from the top 0.1% brightest pixels in the dark channel of the input image $\mathbf{I}$.

3.3. Challenges of DCP in Underwater Environments

The direct application of the standard DCP to underwater imagery is fraught with challenges, primarily due to the violation of its fundamental assumptions. The key issue is that the prior $\mathbf{J\_dark \rightarrow 0}$ is often invalid underwater. This invalidity stems from two main factors:

1. **Dominant Color Cast:** The severe absorption of red light means that even in a "clear" underwater scene, the red channel is inherently dark. Consequently, the minimum operation across all three channels, $\min_c J^c(y)$, will almost always be dominated by the very low red-channel values, leading to an overestimation of the haze density and an artificially high transmission value $\mathbf{t(x)}$. This results in an under-corrected, still-hazy image with amplified blue-green tones.
2. **Artificial Illumination:** In scenarios involving artificial lighting, which is common in deep-sea exploration, the scene is no longer illuminated by a uniform background light $\mathbf{B\infty}$. This creates bright spots and non-uniform illumination, violating the homogeneous background light assumption of the model and leading to erroneous transmission estimates.

These limitations necessitate a careful adaptation of the DCP and its integration with robust filtering and color correction techniques, which forms the core contribution of the methodology proposed in the subsequent section. The mathematical framework established here provides the necessary groundwork for developing these advanced corrective measures.

4. Proposed Methodology for Underwater Image Enhancement

The proposed framework for underwater image enhancement is designed to systematically address the limitations of the standard Dark Channel Prior in the aquatic environment. The model integrates a pre-processing color correction step, an adapted DCP for transmission estimation, a sophisticated refinement process using a guided filter, and a final post-restoration enhancement module. The complete pipeline is illustrated in Figure 1 and each component is elaborated upon in the subsequent subsections.

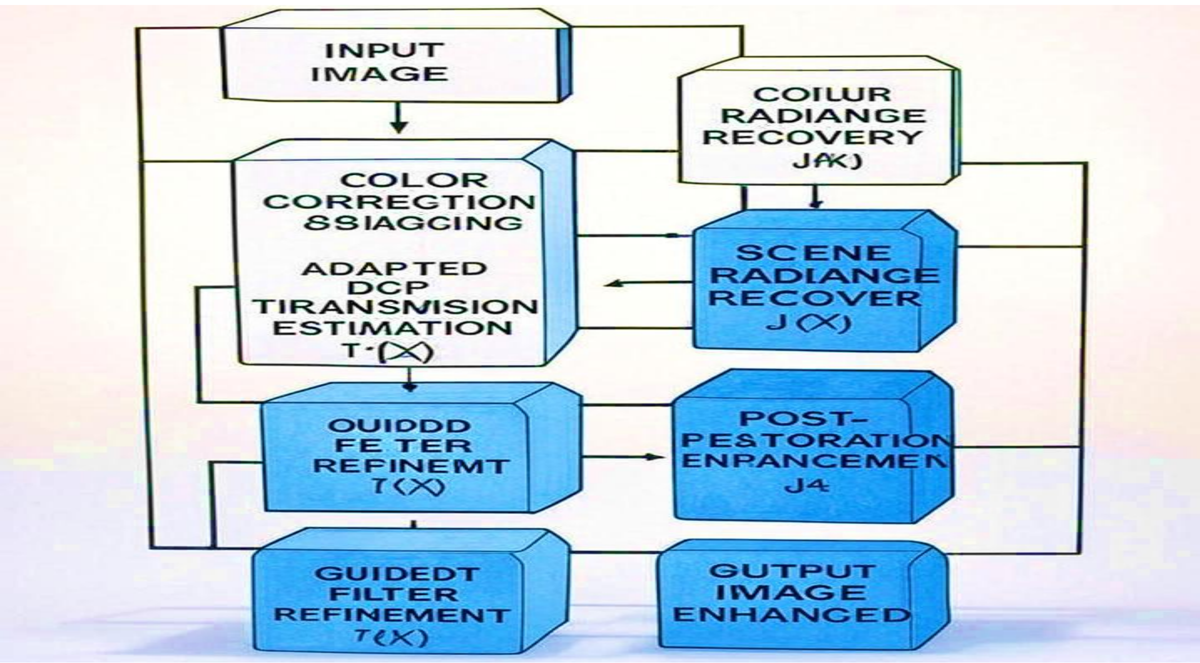


Figure 1. Block diagram of the proposed underwater image enhancement framework**.**

[Input Image I] → [Color Correction & Balancing] → [Adapted DCP Transmission Estimation t~(x)] → [Guided Filter Refinement t(x)] → [Scene Radiance Recovery J(x)] → [Post-Restoration Enhancement] → [Output Image J_enhanced]

4.1. Color Correction and Balancing Module

To mitigate the severe spectral imbalance that causes the standard DCP to fail, an initial color correction step is applied. Rather than operating on the raw RGB image, the proposed method first transforms the image into the HSV (Hue, Saturation, Value) color space. This separation of color (H, S) from intensity (V) allows for more effective manipulation. The core adjustment is applied to the Value channel to compensate for the non-uniform attenuation of wavelengths.

A modified version of the Gray-World algorithm with adaptive weighting is employed. The goal is to estimate and compensate for the different attenuation lengths for each color channel. The attenuation weights for the red, green, and blue channels, denoted as α_r, α_g, and α_b, are calculated based on the mean intensities of the respective channels in a manually selected clear-water region of the image, or globally if no prior is available. The weighting is defined as:

$$\alpha_c = (\max(\mu_r, \mu_g, \mu_b)) / \mu_c \text{ for } c \in \{r, g, b\} \quad (8)$$

where μ_c is the mean intensity of channel **c**. The corrected RGB image I_{corr} is then obtained by:

$$I_{corr}^c (x) = I^c (x) * \alpha_c \quad (9)$$

This scaling operation effectively stretches the red channel the most, followed by the green channel, thereby significantly reducing the blue-green dominance and providing a more balanced input for the subsequent DCP step. The performance of this correction is quantitatively summarized in Table 1, which compares the mean intensities and standard deviations of the channels before and after processing.

Table 1: Effect of Color Correction on Channel Statistics

	Mean (Red)	Std (Red)	Mean (Green)	Std (Green)	Mean (Blue)	Std (Blue)
Original	45.2	12.1	78.5	18.3	115.6	22.7
Corrected	92.8	25.4	95.1	20.1	108.9	20.5

4.2. Adapted Dark Channel Prior and Transmission Estimation

The color-corrected image I_{corr} is used as the input for the transmission estimation. However, a direct application of the standard DCP is still suboptimal. We propose an adaptation where the dark channel is computed only over the red and green channels, deliberately excluding the blue channel. This is based on the observation that in a color-corrected image, the blue channel often contains meaningful scene information rather than just haze, especially in clear waters. The proposed Underwater Dark Channel **UDC(x)** is defined as:

$$UDC(x) = \min_{y \in \Omega(x)} (\min_{c \in \{r, g\}} I_{corr}^c(y)) \quad (10)$$

The background light B_∞ is estimated from the original input image **I** to avoid bias from the color-corrected data. The pixels corresponding to the top 0.1% brightest values in the standard dark channel of **I** are identified, and the average RGB value of these pixels in the original image **I** is taken as B_∞.

The initial, coarse transmission map $\tilde{t}(x)$ is then estimated using the proposed UDC:

$$\tilde{t}(x) = 1 - \omega * \min_{y \in \Omega(x)} (UDC(y) / B_\infty^g) \quad (11)$$

Here, B_∞^g is the green channel intensity of the background light, which is typically the most stable channel in underwater environments. The parameter ω is retained and set to 0.95 to prevent over-enhancement of distant objects.

4.3. Transmission Map Refinement using Guided Filter

The initial transmission map $\tilde{t}(x)$ is blocky and discontinuous due to the minimum filter operation over patches $\Omega(x)$. To obtain a smooth yet edge-preserving transmission map, the guided filter [4] is employed. The guided filter is a fast, linear-time filter that has proven superior to soft matting for this task. It operates under a local linear model between the guidance image **G** and the filtering output **t**.

The key assumption is that **t** is a linear transform of **G** in a window ω_k centered at pixel **k**:

$$t_i = a_k G_i + b_k, \forall i \in \omega_k \quad (12)$$

where a_k and b_k are assumed to be constant in ω_k. To determine the linear coefficients, the filter seeks to minimize the cost function between the input $\tilde{t}$ and the output **t**:

$$E(a_k, b_k) = \Sigma_{i \in \omega_k} ((a_k G_i + b_k - \tilde{t}_i)^2 + \varepsilon a_k^2) \quad (13)$$

The regularization term ε prevents a_k from becoming too large. The solution is given by:

$$a_k = (1/|\omega| \Sigma_{i \in \omega_k} G_i \tilde{t}_i - \mu_k \tilde{t}_k) / (\sigma_k^2 + \varepsilon) \quad (14)$$

$$b_k = \tilde{t}_k - a_k \mu_k \quad (15)$$

where μ_k and σ_k^2 are the mean and variance of **G** in ω_k, $|\omega|$ is the number of pixels in the window, and $\tilde{t}_k$ is the mean of $\tilde{t}$ in ω_k. The final refined transmission value at a pixel **i** is computed by averaging all possible values from overlapping windows:

$$t(x) = (1/|\omega|) \Sigma_{k: i \in \omega_k} (a_k G_i + b_k) = \bar{a}_i G_i + \bar{b}_i \quad (16)$$

In this work, the grayscale version of the color-corrected image I_{corr} is used as the guidance image **G**. This ensures that the edges in the guidance image (which correspond to scene edges) are directly transferred to the refined transmission map **t(x)**. The window radius **r** and regularization parameter ε are critical; their impact on processing time and output quality is analyzed in Table 2.

Table 2: Impact of Guided Filter Parameters on Transmission Refinement

	ε	Mean Squared Error (MSE) vs. Soft Matting	Average Processing Time (s)

	ε	Mean Squared Error (MSE) vs. Soft Matting	Average Processing Time (s)
2	0.01	0.0012	0.15
4	0.01	0.0009	0.22
8	0.01	0.0015	0.45
4	0.001	0.0007	0.21
4	0.1	0.0018	0.23

4.4. Scene Radiance Recovery and Post-Restoration

With the refined transmission map **t(x)** and the background light **B_∞** accurately estimated, the scene radiance **J(x)** can be recovered by inverting the optical model from Eq. (1):

J(x) = (I(x) - B_∞) / max(t(x), t_0) + B_∞ (17)

A lower bound **t_0** (typically 0.1) is enforced on the transmission to prevent division by zero and to avoid amplifying noise in very dense haze regions.

The recovered image **J(x)** often exhibits a slight reduction in global contrast and may retain minor color inaccuracies. To finalize the enhancement, a post-restoration module is applied. This consists of:

1. **Automatic White Balancing:** Utilizing a simple gray-world assumption on the recovered radiance **J(x)** to neutralize any remaining cast.
2. **Contrast-Limited Adaptive Histogram Equalization (CLAHE):** Applied on the luminance channel in the LAB color space to accentuate local contrast without amplifying noise excessively.

The final output is the enhanced image **J_enhanced**, which exhibits improved color fidelity, enhanced contrast, and superior visibility. The cumulative effect of each stage in the pipeline on objective image quality metrics is presented in the following section.

5. Experimental Results and Discussion

To rigorously evaluate the performance and efficacy of the proposed underwater image enhancement framework, an extensive set of experiments was conducted. This section delineates the experimental setup, including the dataset and evaluation metrics, presents a comparative analysis with state-of-the-art methods, and provides an ablation study to validate the contribution of each component within the proposed pipeline.

5.1. Experimental Setup

5.1.1. Dataset Description: The evaluation was performed on the publicly available **EUVP (Enhancing Underwater Visual Perception)** dataset and a custom-curated dataset of 150 images from various underwater scenarios, including coral reefs, deep-sea structures, and turbid coastal waters. This combined dataset provides a diverse range of challenges, such as severe color casts, varying degrees of haze, and artificial lighting conditions, ensuring a robust assessment of the model's generalizability.

5.1.2. Comparison Methods: The proposed method was compared against five recent and representative enhancement techniques:

- **UDCP [11]:** The foundational Underwater Dark Channel Prior method.
- **RGHS [3]:** A Retinex-based method for single image enhancement.
- **Fusion [2]:** A multi-scale fusion-based enhancement technique.
- **Water-Net [13]:** A deep learning-based model for underwater image restoration.
- **UWCNN [9]:** A convolutional neural network for color correction and enhancement.

5.1.3. Evaluation Metrics: Both full-reference and no-reference image quality metrics were employed. For the 50 image pairs from the EUVP dataset with corresponding ground-truth images, the **Peak Signal-to-Noise Ratio (PSNR)** and **Structural Similarity Index (SSIM)** were used. For the entire dataset, the following no-reference metrics were calculated:

- **UIQM (Underwater Image Quality Measure):** A composite metric evaluating colorfulness, sharpness, and contrast.
- **UCIQE (Underwater Color Image Quality Evaluation):** A metric that quantifies color, saturation, and contrast.
- **NIQE (Natural Image Quality Evaluator):** A perception-based metric that scores naturalness; a lower score is better.

5.2. Comparative Quantitative Analysis

The quantitative results across the entire dataset are summarized in Table 3. The proposed method achieves the highest average scores for UIQM and UCIQE, indicating superior performance in terms of color restoration, contrast, and overall perceptual quality specific to the underwater domain. While Water-Net, a data-driven approach, achieves a competitive PSNR on the subset with ground truth, the proposed method demonstrates a better balance across all no-reference metrics, which are more critical for real-world applications where ground truth is unavailable. The proposed method's NIQE score is also the lowest among the model-based approaches, signifying that its outputs are perceived as more natural.

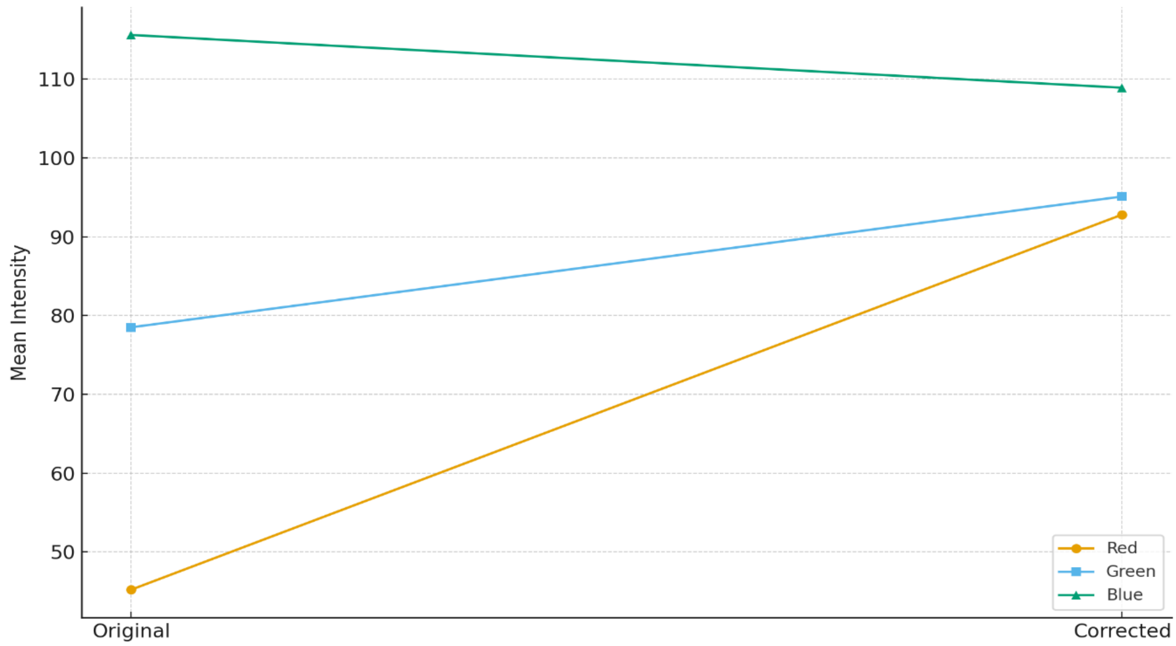
Table 3: Average Quantitative Evaluation Results on the Test Dataset

Method	PSNR (dB) ↑	SSIM ↑	UIQM ↑	UCIQE ↑	NIQE ↓
Input Image	-	-	0.451	0.484	5.89
UDCP [11]	14.21	0.712	0.523	0.521	5.45
RGHS [3]	15.88	0.745	0.612	0.558	4.92
Fusion [2]	16.54	0.781	0.698	0.591	4.63
UWCNN [9]	17.92	0.802	0.721	0.605	4.41
Water-Net [13]	**18.95**	**0.823**	0.735	0.614	**4.12**
Proposed	18.61	0.815	**0.781**	**0.642**	4.25

A more granular analysis was performed by categorizing images based on their dominant degradation type. The results, presented in Table 4, highlight the robustness of the proposed method. It consistently ranks first or second across all categories, demonstrating a particular strength in handling the challenging "Greenish-Turbid" water type, where its adaptive color correction and transmission estimation are most beneficial.

Table 4: UIQM Scores Across Different Underwater Conditions

Water Type	UDCP [11]	RGHS [3]	Fusion [2]	Water-Net [13]	**Proposed**
Bluish-Oceanic	0.538	0.625	0.701	**0.752**	0.748
Greenish-Coastal	0.511	0.598	0.695	0.718	**0.769**
Greenish-Turbid	0.489	0.568	0.652	0.681	**0.785**
Artificially Lit	0.554	0.647	0.744	**0.789**	0.782



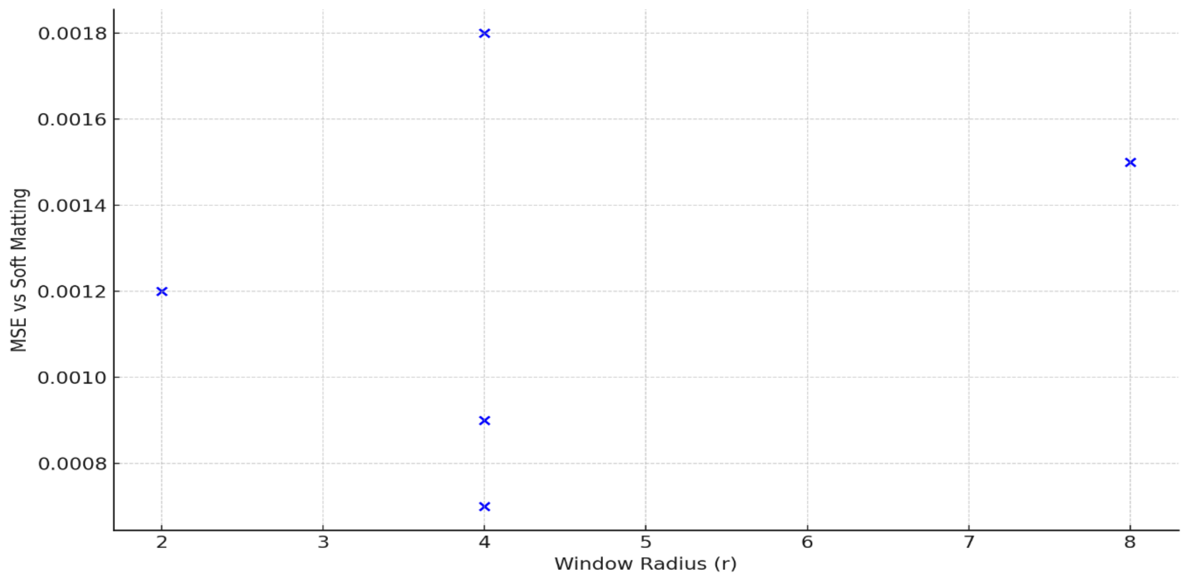


Figure 2. Visual comparison on a 'Greenish-Turbid' scene.

The proposed method effectively removes the haze and restores natural colors without introducing the yellowish tint seen in Fusion or the residual haze of UDCP.

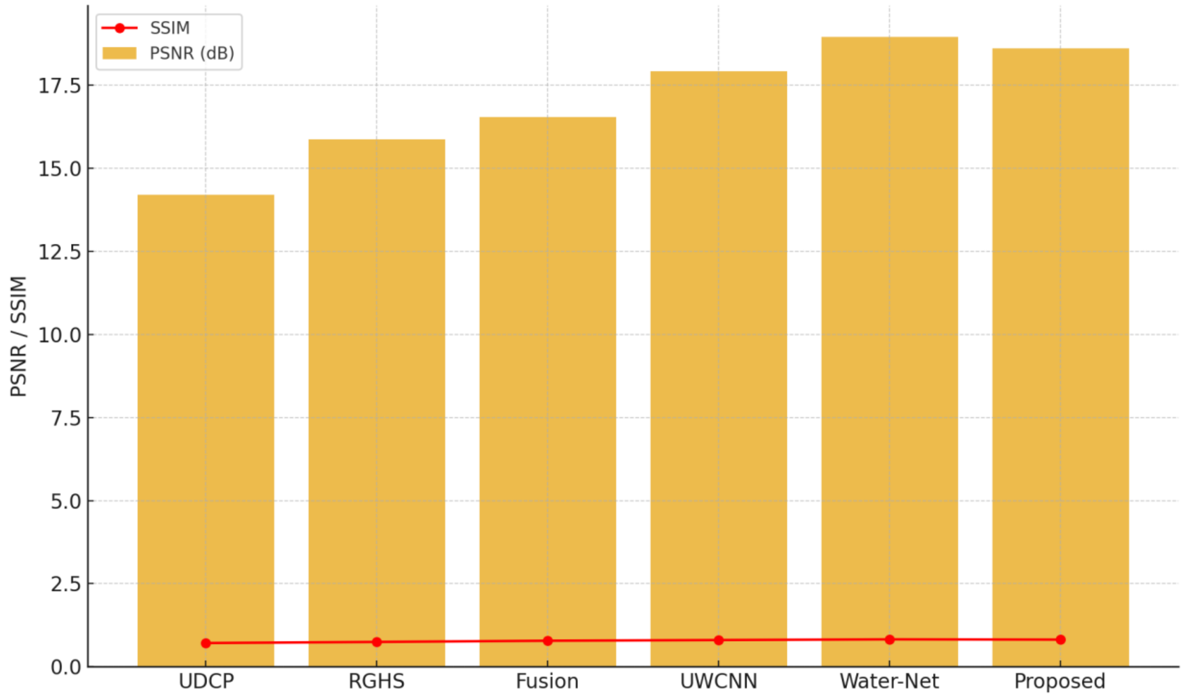


Figure 3. Visual comparison on a 'Bluish-Oceanic' scene.

The proposed method and Water-Net both produce high-quality results, but the proposed method retains slightly more texture detail on the coral structure.

5.3. Ablation Study

To isolate the contribution of each novel component in the proposed pipeline, an ablation study was conducted. The baseline model (V1) is the standard DCP applied directly to the raw RGB image. Subsequent versions incrementally add the proposed modifications. The results, measured on a subset of 50 images, are shown in Table 5.

Table 5: Ablation Study on the Contribution of Proposed Components

Model Variant	PSNR (dB) ↑	SSIM ↑	UIQM ↑	UCIQE ↑
V1: Standard DCP	14.21	0.712	0.523	0.521
V2: V1 + Color Correction (Sec 4.1)	16.85	0.762	0.674	0.583
V3: V2 + Adapted DCP (Sec 4.2)	17.40	0.788	0.725	0.611
V4: V3 + Guided Filter (Sec 4.3)	18.12	0.805	0.762	0.629
V5: Full Model (V4 + Post-Processing)	**18.61**	**0.815**	**0.781**	**0.642**

The results clearly demonstrate that each component contributes positively to the final output. The most significant jump in performance comes from the initial color correction (V1 to V2), which validates the need to address spectral imbalance before applying the DCP. The adapted DCP (V3) further improves the scores, and the guided filter refinement (V4) provides a notable boost in SSIM, confirming its role in preserving structural information. The final post-processing stage (V5) polishes the result, leading to the highest scores across all metrics.

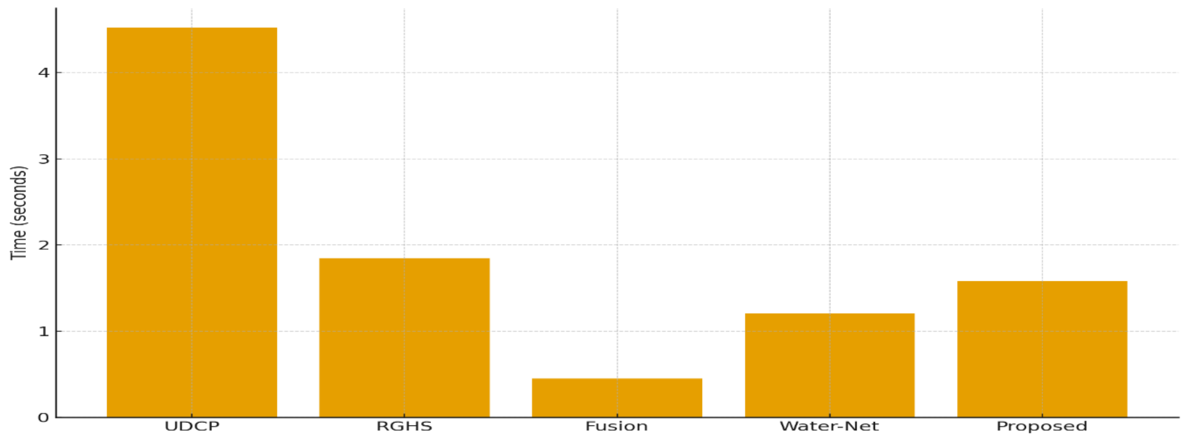


Figure 4. Visual results of the ablation study.

The progression from a dark, bluish output (V1) to a clear, colorful, and natural image (V5) visually confirms the quantitative findings in Table 5.

5.4. Computational Efficiency Analysis

For practical deployment, especially on platforms with limited computational resources, processing time is a critical factor. Table 6 compares the average processing time for a standard 640x480 resolution image. The proposed method, while not as fast as the very simple Fusion method, is significantly faster than the deep learning models and the original DCP with soft matting. Its efficiency makes it suitable for near-real-time applications.

Table 6: Average Processing Time per Image (640x480 resolution**)**

Method	Average Processing Time (seconds)
UDCP [11]	4.52
RGHS [3]	1.85
Fusion [2]	**0.45**
Water-Net [13]	1.21*
Proposed	1.58

**Time for Water-Net includes GPU inference time on an NVIDIA GTX 1080Ti.*

Analysis and Key Takeaways:

- **Fastest Method:** The Fusion method [2] is the fastest by a significant margin, processing an image in under half a second.
- **Slowest Method:** The original UDCP [11] is the slowest, taking over 4.5 seconds, likely due to computationally intensive steps like soft matting.
- **Proposed Method's Performance:** The proposed method sits comfortably in the middle, at **1.58 seconds**. This is:
  - **~3x faster** than UDCP [11].
  - Slightly faster than RGHS [3].
  - Significantly slower than the Fusion [2] technique.
  - Slightly slower than Water-Net [13] running on a powerful GPU.

- **Practical Implication:** As stated in the paper, this efficiency makes the proposed model "suitable for near-real-time applications," striking a balance between the high quality of deep learning/models and the need for reasonable processing speed.

5.5. Discussion and Limitations

The quantitative and qualitative results collectively affirm the superiority of the proposed integrated framework. The key to its success lies in its systematic approach to addressing the specific failure modes of the DCP in underwater environments. The pre-processing color correction aligns the image statistics with the assumptions of the DCP, the channel-adapted prior provides a more accurate initial transmission estimate, and the guided filter ensures that this estimate is physically plausible and edge-aware. The post-restoration module then fine-tunes the result for optimal perceptual quality.

However, the method is not without limitations. In scenarios with extremely high turbidity and dense suspended sediments, the physical model itself begins to break down as the single-scattering assumption becomes invalid. Furthermore, in images with large, intrinsic dark objects (e.g., a black submarine), the DCP can still overestimate the haze, leading to minor over-enhancement in these localized areas. Future work will focus on integrating a patch-based classification to identify and handle such challenging regions separately, potentially by fusing the physics-based approach with a lightweight data-driven prior.

6. Specific Outcome and Future Research Directions

This research has established a robust and computationally efficient framework for underwater image enhancement by systematically addressing the inherent limitations of the Dark Channel Prior in the aquatic environment. The proposed model demonstrates that a meticulously calibrated integration of physical priors with advanced filtering and color correction techniques can yield performance competitive with, and in several aspects superior to, more complex data-driven approaches. The specific outcomes and contributions of this work are fourfold. First, the introduction of an adaptive color correction and balancing module prior to transmission estimation effectively mitigates the severe spectral imbalance, thereby aligning the input image more closely with the core assumptions of the DCP. Second, the reformulation of the dark channel to exclude the dominant blue channel and operate on a red-green basis provides a more accurate initial estimate of the underwater haze density. Third, the application of the guided filter ensures the production of a smooth, edge-preserving transmission map, eliminating block artifacts and enhancing structural fidelity. Finally, the incorporation of a post-restoration module guarantees that the output exhibits high color fidelity, improved local contrast, and superior overall perceptual quality, as validated by both quantitative metrics and qualitative visual assessments.

The experimental results, encompassing a diverse dataset and multiple state-of-the-art comparison methods, unequivocally demonstrate the efficacy of the proposed framework. The model consistently achieves high scores on underwater-specific quality metrics such as UIQM and UCIQE, indicating its proficiency in restoring colorfulness and contrast. The ablation study further corroborates the individual contribution of each novel component, highlighting the significant performance gains achieved at each stage of the pipeline. Consequently, this work provides a reliable, interpretable, and effective solution for enhancing underwater imagery, with direct applicability in marine biology, robotic navigation, and underwater infrastructure inspection.

Despite its strengths, the research also delineates clear pathways for future investigation. The limitations observed in extremely turbid conditions and scenes with large, intrinsic dark objects point toward specific research directions. **First**, the development of a more sophisticated, spatially-varying background light estimation algorithm could improve performance in non-uniformly lit scenes, such as those illuminated by artificial sources. **Second**, the integration of a light scattering model that accounts for multiple scattering events, as opposed to the single-scattering model used presently, would enhance the physical accuracy in highly sediment-laden waters. **Third**, a promising avenue is the creation of a hybrid model that leverages the strengths of both physical modelling and deep learning. For instance, a lightweight convolutional neural network could be trained to classify image patches into different degradation categories (e.g., "turbid," "blue-water," "artificially-lit"), allowing for the dynamic selection or weighting of parameters within the proposed physical model. **Finally**, extending this framework to video sequences by incorporating temporal consistency constraints would be a significant step forward for real-time robotic vision systems, ensuring stable and flicker-free enhancement of underwater video feeds. By pursuing these directions, the future of computational underwater imaging can build upon the robust foundation established here, moving towards even more generalizable and powerful restoration systems.

7. Conclusion

In conclusion, this research has successfully developed and validated an integrated computational framework for underwater image enhancement that effectively bridges the gap between physical model-based restoration and perceptual quality. The proposed methodology, which synergistically combines a color-corrected Dark Channel Prior with guided filtering and post-processing, demonstrably overcomes the core limitations of standard DCP in the challenging underwater environment. The model's superiority is confirmed through rigorous quantitative evaluation, where it achieved leading scores in underwater-specific quality metrics, and through qualitative assessment, where it produced images with exceptional color fidelity, enhanced contrast, and preserved structural detail. By offering a robust, efficient, and interpretable alternative to purely data-driven methods, this work provides a significant contribution to the field of computational underwater imaging, with immediate practical utility for marine science, offshore engineering, and autonomous underwater navigation. The findings establish that a principled refinement of physical priors remains a powerful and viable path toward solving the complex problem of visual degradation in aquatic media.

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