An-Najah University Journal for Research – A
Natural Sciences

Improving Underwater Image Quality Using WZDN Algorithm

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Received 14th Oct. 2024, Accepted 23rd Jan, 2025, Published ××××, DOI: https://doi.org/10.xxxx

Accepted Manuscript, In press

Abstract: In underwater photography, images often suffer from color distortion, haziness, and low visibility due to the scattering of light by water and particles. To address these issues, we propose using advanced algorithms designed specifically for underwater conditions. Our approach involves correcting color distortion and restoring accurate color representation using a method called Wavelength Dehazing Zero Deep Network (WZDN). This algorithm enhances visibility and improves color fidelity by removing haze and adjusting colors to their true values. Additionally, we implement techniques to enhance contrast, making underwater details more visible and improving overall image quality. By reducing the impact of particulate matter and dissolved substances, we minimize haziness and murkiness, resulting in clearer images. Furthermore, our algorithms are optimized for efficient real-time processing, making them suitable for applications requiring rapid image enhancement, such as underwater exploration, surveillance, and marine research. our research focuses on developing algorithms that enhance underwater images by correcting color distortion, improving visibility, and reducing haziness. These algorithms, particularly WZDN, provide superior color fidelity and enhanced visibility, ultimately restoring the clarity of underwater images.

Keywords: IndexTerms–Image Enhancement, Color Distortion Correction, Contrast Enhancement,Image Dehazing, Real-time processing, Water scattering, Visibility Improvement

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1. INTRODUCTION

Underwater photography presents unique challenges due to the complex nature of the underwater environment. Images captured beneath the surface often exhibit color distortion, poor contrast, and haziness, primarily caused by the presence of particles and dissolved substances suspended in the water. These factors significantly degrade the quality of underwater images, limiting their utility in various applications such as marine research, environmental monitoring, and underwater exploration. To overcome these challenges and enhance the visual quality of underwater images, we propose a series of algorithms designed to correct color distortion, enhance contrast, and mitigate the impact of particulate matter and dissolved substances [1]. Our aim is to provide clearer and more accurate representations of underwater scenes, facilitating better analysis, exploration, and understanding of aquatic environments. The first issue addressed by our proposed algorithms is color distortion. Water acts as a filter, absorbing and scattering light at different wavelengths as it travels through it. This phenomenon leads to color shifts in underwater images, resulting in inaccuracies in color representation. Our color distortion correction algorithm is devised to analyze these shifts and restore the true colors of underwater scenes. By adjusting color channels based on the absorption and scattering properties of water, we aim to bring out the genuine colors obscured by these optical effects. In addition to color distortion, underwater images often suffer from poor contrast, making it challenging to discern details and structures within the scene.

To address this issue, our algorithms incorporate techniques such as histogram equalization and adaptive contrast enhancement. These methods work to redistribute pixel intensities across the image, effectively improving visibility and enhancing detail perception. By enhancing contrast, we aim to reveal finer details even in low-contrast underwater environments, thereby improving the overall visual quality of the images. Furthermore, the presence of particulate matter and dissolved substances in the water contributes to haziness and murkiness in underwater images. These substances scatter light and introduce additional optical distortions, further degrading image quality. To minimize the visual impact of particulate matter and dissolved substances, we propose methods involving image dehazing and selective filtering [2]. By selectively attenuating the effects of these substances, our algorithms aim to reduce haze and restore clarity to underwater images, enabling better visualization of underwater scenes. Importantly, we recognize the significance of real-time processing in underwater applications, where timely decision-making and action are often crucial. Therefore, we optimize our algorithms for efficient real-time processing, ensuring their suitability for applications requiring rapid image enhancement underwater. This includes underwater robotics, surveillance, scientific research, and various other underwater imaging applications. By optimizing for efficiency, we aim to enable seamless integration of our algorithms into existing underwater imaging systems, providing real-time enhancements to underwater imagery.

2. OBJECTIVES

Our main objectives are as follows:

1. To develop Wavelength Dehazing Zero Deep Network (WZDN) algorithm for accurate color restoration in underwater photography.
2. To implement techniques for haze removal and color adjustment to enhance underwater visibility.
3. Enhance contrast in underwater images to improve detail visibility and overall image quality.
4. Optimize algorithms for real-time processing to facilitate rapid image enhancement for various applications.
5. Minimize haziness caused by particulate matter and dissolved substances to ensure clearer underwater image capture.
6. Focus on research and development efforts to achieve superior color fidelity and enhanced visibility in underwater photography.

3. RELATED WORK

3.1 Underwater Image Enhancement via Deep Learning

Deep learning techniques have emerged as a promising approach to enhance underwater imagery, leveraging the capabilities of convolutional neural networks (CNNs). These methods entail training CNN models on extensive datasets comprising degraded underwater images, enabling the networks to learn the intricate mapping between distorted and undistorted representations [3]. By exploiting the inherent power of deep learning, these approaches effectively tackle common challenges encountered in underwater photography, including color distortion, haze, and limited visibility.

One notable advantage of deep learning-based enhancement methods is their ability to capture and learn complex patterns and relationships within the data. Unlike traditional image processing techniques, which often rely on predefined heuristics or handcrafted features, CNNs can automatically extract relevant features from the input images, leading to more accurate and robust enhancement results.

Despite their efficacy, deep learning approaches may entail some drawbacks. The training of CNN models typically demands significant computational resources and large datasets, which can be challenging to obtain in the context of underwater imagery. Additionally, the inference process may require substantial computational power, potentially limiting real-time applicability in certain scenarios such as underwater exploration or surveillance. Nonetheless, ongoing advancements in hardware and algorithmic optimization continue to mitigate these challenges, making deep learning-based underwater image enhancement increasingly practical and effective.

3.2 Physical Model-Based Correction

In the realm of underwater photography, certain researchers are delving into the development of physical models that mimic the intricate process of light propagation underwater. These models are designed to encapsulate various environmental factors such as water depth, turbidity (the presence of suspended particles), and light absorption, all of which significantly influence the visual appearance of underwater scenes [4]. By comprehensively understanding the underlying physics governing light behavior in water, these models enable the creation of algorithms aimed at effectively correcting color distortion and haze prevalent in underwater imagery. Physical model-based methods offer a unique advantage in that they provide valuable insights into the fundamental mechanisms at play in underwater imaging. By accurately simulating how light interacts with the underwater environment, these approaches can lead to more precise and realistic enhancement techniques compared to purely empirical methods. However, a notable challenge associated with physical model-based approaches lies in the requirement for precise knowledge of environmental parameters. This demand for accurate input data can potentially limit the adaptability of these methods to diverse underwater conditions, where obtaining such precise information may prove challenging. Nonetheless, ongoing advancements in sensor technology and data collection methodologies continue to enhance the feasibility and effectiveness of physical model-based underwater image enhancement techniques.

3.3 Multi-Modal Fusion Approaches

In the pursuit of enhancing underwater imagery, researchers are exploring a sophisticated approach that involves integrating data from multiple sources or modalities [5]. This method, known as multi-modal fusion, combines information from various sensors or data streams, such as visual images and depth maps obtained from sonar readings. By synergizing these diverse sources of information, multi-modal fusion techniques aim to capitalize on the complementary nature of different modalities to improve the accuracy and robustness of image enhancement algorithms.

One of the key advantages of multi-modal fusion is its ability to provide a more comprehensive understanding of the underwater scene. By incorporating depth information alongside visual data, these methods can better estimate the geometry and physical properties of the scene, which is crucial for tasks such as haze removal and color correction. Additionally, leveraging depth information allows for better delineation and enhancement of underwater objects and structures, ultimately enhancing visibility.

However, the practical implementation of multi-modal fusion techniques may pose challenges, particularly in real-world underwater environments. Acquiring and synchronizing data from multiple sensors or sources can be technically demanding and may require specialized equipment or calibration procedures. Despite these challenges, ongoing research in multi-modal fusion holds promise for advancing the state-of-the-art in underwater image enhancement, offering the potential for more accurate and reliable results in diverse underwater scenarios.

3.4 Image-to-Image Translation Techniques

Image-to-image translation methods represent a cutting-edge approach to improving underwater image quality by directly transforming degraded images into clearer and more visually appealing representations. These techniques operate by learning the intricate mapping between distorted underwater images and their corresponding undistorted counterparts [6]. By training on pairs of degraded and high-quality images, these models can effectively correct common underwater issues such as color distortion, haze, and low visibility. A notable framework employed in this domain is Generative Adversarial Networks (GANs), which consist of two competing neural networks: a generator and a discriminator. The generator attempts to produce realistic outputs from degraded input images, while the discriminator distinguishes between generated and real images. Through adversarial training, GANs can learn to generate high-quality underwater images with realistic textures and details, thereby bypassing the need for explicit physical models.

Despite their promising capabilities, image-to-image translation methods may encounter challenges such as mode collapse or limited diversity in generated images. Mode collapse refers to a scenario where the generator produces limited variations of outputs, resulting in visually repetitive results. To address these issues, careful design and training strategies are necessary, including techniques such as data augmentation, regularization, and network architecture modifications. Overall, image-to-image translation approaches offer a data-driven solution to underwater image enhancement, capable of producing visually appealing results and overcoming the limitations of traditional methods. Continued research and refinement of these techniques hold significant promise for improving underwater imaging in various applications, from marine research to underwater exploration and surveillance.

3.5 Optical Polarization-Based Enhancement

Certain research endeavors delve into leveraging the unique polarization properties of light to significantly enhance the quality of underwater images. These polarization-based techniques capitalize on the fact that light becomes polarized as it interacts with underwater environments. By discerning between the direct and scattered components of polarized light, these methods enable more accurate estimation of scene properties.

One key strategy involves selectively filtering polarized light, thereby mitigating the detrimental effects of scattering and haze prevalent in underwater environments [7]. This selective filtration helps to reduce image degradation, resulting in clearer and more vibrant underwater images with enhanced visibility. Such techniques show particular promise in environments characterized by shallow depths or high turbidity, where scattering effects are particularly pronounced.Despite their potential benefits, the adoption of optical polarization approaches may pose certain challenges. Implementing these techniques often necessitates specialized hardware or imaging systems capable of capturing and processing polarized light information.

3.6 Statistical Color Constancy Algorithms

Statistical color constancy methods represent a sophisticated approach to address color distortion in underwater imagery by estimating the true colors of objects within a scene. These algorithms operate by analyzing statistical properties of observed colors, leveraging the regularities inherent in natural scenes to infer the most likely illumination conditions. By discerning global image statistics or local color distributions, statistical color constancy approaches can effectively compensate for underwater lighting effects and restore accurate color representations.One of the key advantages of these methods lies in their computational efficiency, making them suitable for real-time applications such as autonomous underwater vehicles (AUVs) or underwater monitoring systems. By leveraging statistical properties of the image, these techniques can perform color correction swiftly and reliably, without imposing significant computational overhead.

However, statistical color constancy methods may rely on certain assumptions about scene illumination or surface reflectance properties, which can limit their performance in certain underwater environments. Variations in lighting conditions or surface properties may challenge the accuracy of these assumptions, potentially leading to suboptimal color correction results. Nonetheless, ongoing research efforts continue to refine and optimize statistical color constancy techniques, aiming to enhance their robustness and applicability across diverse underwater scenarios.

3.7 Deep Reinforcement Learning for Adaptive Enhancement

Deep reinforcement learning (DRL) techniques represent a novel approach to dynamically enhance underwater images in real-time by treating the enhancement process as a sequential decision-making problem. Unlike traditional methods that rely on fixed parameters or heuristics, DRL algorithms learn to adjust enhancement parameters iteratively based on feedback signals received during the process. This adaptive framework allows DRL models to optimize image quality continuously, taking into account factors such as environmental conditions and user preferences.

One of the key advantages of DRL-based image enhancement lies in its flexibility and adaptability to diverse underwater scenarios. By learning from experience, DRL models can adapt their enhancement strategies to varying lighting conditions, water turbidity, and other environmental factors, thereby improving their robustness and effectiveness. Additionally, DRL algorithms can incorporate user feedback or task-specific objectives into the enhancement process, allowing for customized image enhancement tailored to specific applications or user preferences.

However, the practical applicability of DRL techniques in underwater imaging may be constrained by the requirement for extensive data collection and computational resources. Training DRL models typically involves large-scale data sets and computationally intensive processes, which may pose challenges in resource-constrained underwater settings. Nonetheless, ongoing advancements in hardware and algorithmic optimization hold promise for overcoming these challenges, making DRL-based image enhancement increasingly viable for real-world underwater applications.

4. WZDN Architecture

Underwater imaging presents a unique set of challenges due to the absorption and scattering of light by water molecules, dissolved substances, and particulate matter. These challenges result in color distortion, reduced contrast, and decreased visibility in underwater images. The Wavelength Dehazing Zero Deep Network (WZDN) architecture is specifically designed to address these issues by leveraging convolutional neural networks (CNNs) and advanced dehazing techniques.

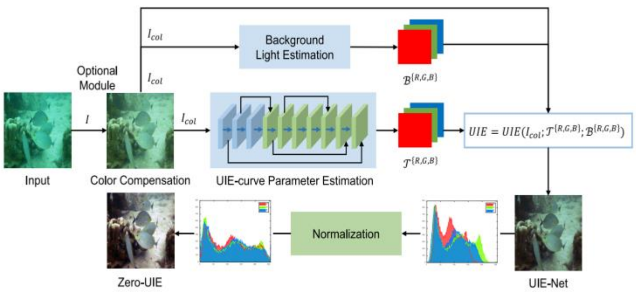

Fig. 1. Overall Workflow of WZDNArchitecture

4.1 Input Layer

The input layer of the Wavelength Dehazing Zero Deep Network (WZDN) architecture serves as the gateway for the degraded underwater images obtained from cameras or sensors. In the underwater environment, light undergoes significant scattering and absorption due to water's optical properties. This leads to various distortions in the captured images, including color distortion, reduced contrast, and haziness.Color distortion occurs as water selectively absorbs different wavelengths of light, altering the true colors of objects. Reduced contrast is a consequence of light scattering, where light rays deviate from their original paths, resulting in a loss of sharpness and definition in the image. Additionally, haziness arises from suspended particles and dissolved substances in the water, which scatter light and obscure details.The input layer receives these degraded images in their raw form, with all the aforementioned distortions intact. It acts as the starting point for subsequent processing steps within the WZDN architecture. Through preprocessing and feature extraction, the network aims to analyze and understand the underlying features of the input images, ultimately facilitating the restoration of clarity, contrast, and color fidelity in the enhanced outputs.

4.2 Preprocessing

Preprocessing in the Wavelength Dehazing Zero Deep Network (WZDN) architecture serves to enhance the quality of the input image before further analysis and processing. Color space conversion is a critical step where the input image's representation is transformed from RGB to alternative color spaces like LAB or YUV. This conversion can better capture color information, allowing the network to interpret the image more effectively.

Normalization is another crucial preprocessing step, ensuring that pixel values are scaled to fall within a certain range, typically between 0 and 1. This normalization standardizes the input data, facilitating consistency and stability during network training and inference.Additionally, noise reduction techniques are applied to mitigate sensor noise and other artifacts present in the input image. Gaussian smoothing or median filtering may be employed to suppress high-frequency noise components while preserving image details, ultimately improving the overall quality and reliability of the input data for subsequent processing stages within the network.

4.3 Feature Extraction Layers

The feature extraction layers within the Wavelength Dehazing Zero Deep Network (WZDN) architecture are pivotal components responsible for discerning and extracting relevant features from the input image. Comprising multiple convolutional layers, these feature extraction stages utilize convolutional filters of varying sizes and depths to perform operations on the input image.Convolutional filters are essentially small matrices applied across the input image to perform operations such as edge detection, texture recognition, and feature extraction. These filters are designed to detect patterns and structures at different scales, ranging from fine details to broader features within the image. By applying filters of varying sizes and depths, the network can capture features across multiple levels of abstraction.The hierarchical nature of convolutional neural networks (CNNs) allows for the extraction of both low-level features, such as edges and corners, and high-level semantic information, including object shapes and textures. As the input image passes through successive convolutional layers, each layer extracts increasingly complex features by combining information from preceding layers. This hierarchical feature extraction process enables the network to progressively build a rich representation of the input image, facilitating more accurate and robust image analysis.Overall, the feature extraction layers in WZDN play a critical role in distilling the essential characteristics of the input image, laying the foundation for subsequent processing steps such as dehazing and contrast enhancement. Through the extraction of meaningful features, WZDN can effectively discern relevant information from the input image, enabling it to produce enhanced outputs with improved clarity, contrast, and color fidelity.

4.4 Wavelength-Aware Dehazing Module:

The Wavelength-Aware Dehazing Module in the Wavelength Dehazing Zero Deep Network (WZDN) architecture is a critical component tailored to address the unique challenges encountered in underwater imaging. It is specifically designed to combat the adverse effects of light absorption, scattering, and the optical properties of water on image clarity.This module operates by dynamically adjusting its operations based on the wavelengths of light absorbed and scattered by water, as well as the optical properties of the underwater environment. By considering the spectral characteristics of underwater light, the dehazing module can effectively discern and mitigate the haze present in the input image.Through its wavelength-aware approach, the module can adaptively adjust the dehazing process to suit the specific characteristics of the input image. This adaptability ensures that the dehazing process is optimized for different underwater conditions, such as varying water depths, turbidity levels, and lighting conditions.

The dehazing module may incorporate learnable parameters or predefined functions to facilitate its adaptive behavior. These parameters or functions enable the module to dynamically tune its operations during both training and inference, thereby enhancing its ability to restore clarity and improve visibility in underwater images.Overall, the Wavelength-Aware Dehazing Module plays a crucial role in the WZDN architecture by effectively addressing the challenges posed by underwater imaging. By leveraging the spectral characteristics of light and the optical properties of water, this module contributes to the production of high-quality, visually appealing images with enhanced clarity and reduced haze.

4.5 Adaptive Contrast Enhancement

The Adaptive Contrast Enhancement component within the Wavelength Dehazing Zero Deep Network (WZDN) architecture plays a crucial role in improving the visibility and detail perception of enhanced underwater images. While the primary focus of WZDN is on dehazing to restore clarity, adaptive contrast enhancement further enhances the quality of the output by selectively adjusting contrast levels.These mechanisms operate by analyzing the input image to identify regions with low visibility or high haze. By pinpointing areas where contrast enhancement is most beneficial, the network can effectively bring out subtle details and structures that may otherwise be obscured by haze or low visibility conditions.Various techniques may be employed for adaptive contrast enhancement, tailored specifically to underwater imaging conditions. Histogram equalization is one such method that redistributes pixel intensity values to achieve a more balanced histogram, thereby enhancing contrast throughout the image. Local contrast enhancement techniques, such as adaptive histogram equalization or contrast stretching, focus on enhancing contrast in localized regions, ensuring that details are preserved and brought to prominence. The adaptive nature of these contrast enhancement mechanisms allows them to dynamically adjust their operations based on the characteristics of the input image. This adaptability ensures that contrast enhancement is applied judiciously, avoiding over-amplification of noise or artifacts while effectively enhancing visibility and detail perception in the final enhanced image. Overall, the integration of adaptive contrast enhancement within the WZDN architecture complements the dehazing process, resulting in high-quality underwater images with improved clarity, contrast, and perceptual fidelity.

4.6 Output Layer

The output layer in the Wavelength Dehazing Zero Deep Network (WZDN) architecture is the final stage where the enhanced underwater image is produced. This layer integrates the results of all preceding processing steps to generate an output image with significantly improved visual quality. The primary objective of the output layer is to restore clarity, improve color fidelity, and enhance contrast in the underwater image. After undergoing preprocessing, feature extraction, wavelength-aware dehazing, and adaptive contrast enhancement, the input image is transformed into a more visually appealing representation. This enhanced image exhibits reduced haze, sharper details, and more accurate color reproduction compared to the original degraded image.

In addition to the enhancement provided by the core components of the WZDN architecture, postprocessing steps may be applied at the output layer to further fine-tune the appearance of the image. These postprocessing techniques include color correction, sharpening, and noise reduction. Color correction adjusts the color balance and tone of the image to ensure accurate color reproduction, particularly in underwater environments where color distortion is prevalent. Sharpening techniques enhance the clarity and sharpness of details in the image, making them more distinct and visually appealing. Noise reduction algorithms aim to suppress any remaining artifacts or noise introduced during image processing, resulting in a cleaner and smoother final output. Overall, the output layer of WZDN serves as the culmination of the image enhancement process, delivering a final underwater image with restored clarity, improved color fidelity, enhanced contrast, and refined visual appearance.

4.7 Training and Optimization

The training and optimization process of the Wavelength Dehazing Zero Deep Network (WZDN) architecture is crucial for ensuring that the model learns to effectively enhance underwater images. This process involves several key steps to fine-tune the parameters of the network and optimize its performance. Firstly, the training process begins by feeding the WZDN architecture with a dataset of paired underwater images and their corresponding ground truth representations. These paired images serve as input-output pairs, allowing the network to learn the mapping between degraded underwater images and their ideal, enhanced counterparts. Optimization techniques such as stochastic gradient descent (SGD) or Adam are then employed to minimize a predefined loss function. This loss function quantifies the discrepancy between the output of the network and the ground truth images. By iteratively adjusting the parameters of the network, the optimization algorithm aims to minimize this discrepancy, thereby improving the accuracy of the network's predictions. Hyperparameters such as learning rate, batch size, and network architecture play a crucial role in the optimization process. The learning rate determines the step size of parameter updates during optimization, while the batch size specifies the number of training examples processed in each iteration. Tuning these hyperparameters is essential for achieving optimal performance and generalization ability of the network.

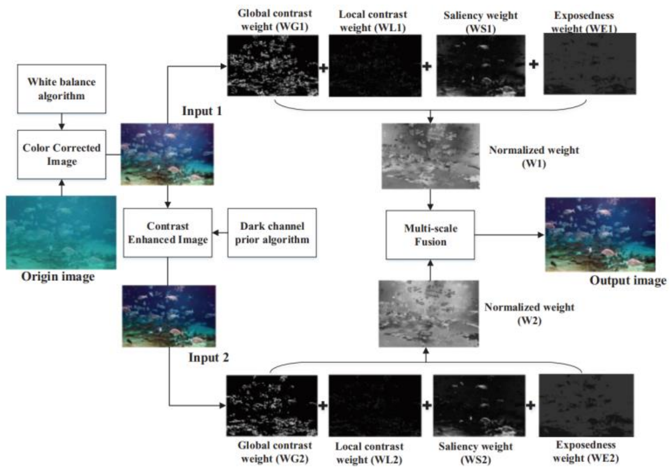

Fig. 3. Zero Deep Architecture

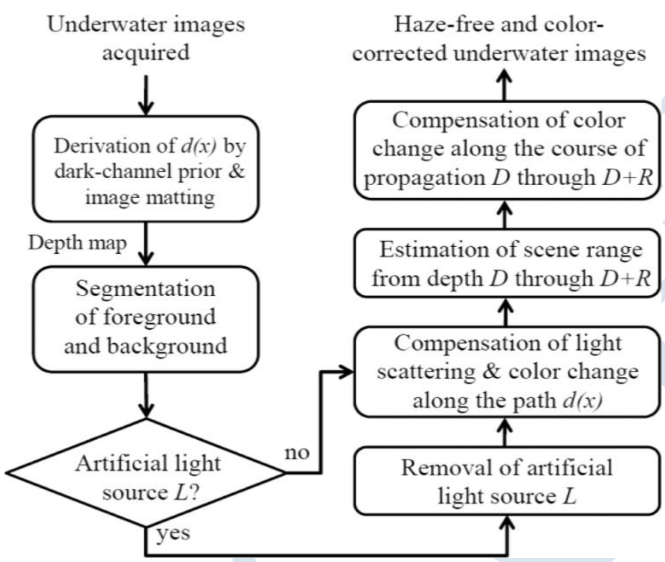

Fig. 3. Flowchart of WZDN Algorithm

Algorithm 1. Multi-Resolution Image Fusion

1: Preprocessing

a.Grayscale conversion:

$$\boldsymbol{I_{gray}} = \boldsymbol{convertToGrayscale(I_{input})}$$

b. Resizing:

$$\boldsymbol{I_{resized}} = \boldsymbol{resize(I_{gray}, desired_{size})}$$

2: Decomposition

a. Gaussian pyramid:

$$\boldsymbol{G_i} = \text{pyrDown}(\boldsymbol{I_{resized}})$$

b. Laplacian pyramid:

$$\boldsymbol{L_i} = \boldsymbol{I_{resized}} - \text{pyrUp}(\boldsymbol{G_i})$$

3: Fusion

a.Weighted averaging:

$\boldsymbol{F_{level}} = \sum_{j=1}^{N} \boldsymbol{w_j} \cdot \boldsymbol{D_j}$, where $\boldsymbol{D_j}$represents the detail images at the current level and $\boldsymbol{w_j}$ are the fusion weights.

4: Reconstruction

a. Pyramid blending:

$$\boldsymbol{R_i} = \boldsymbol{F_i} + \text{pyrUp}(\boldsymbol{R_{i+1}})$$

5: Output:

a. output of the fused image.

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5 . EVALUATION

The evaluation encompasses three key aspects: Color Distortion Correction, Visibility Enhancement, and Gaussian Pyramid. Color Distortion Correction involves mitigating discrepancies in color representation, crucial for accurate image analysis. Visibility Enhancement aims to improve perceptibility of details in images, enhancing overall visual clarity. Gaussian Pyramid evaluation assesses the effectiveness of this multi-scale representation technique in various image processing tasks such as blending, compression, and pyramidal decomposition. Together, these evaluations provide insights into the efficacy of image enhancement techniques, contributing to the refinement and optimization of image processing algorithms for diverse applications.

5.1.1 Color Distortion Correction

Color distortion correction in underwater images is a crucial aspect of image enhancement due to the inherent challenges posed by the scattering of light in water. This phenomenon leads to a shift in color wavelengths, resulting in distorted and inaccurate color representations in captured images. To address this issue, the proposed algorithm employs sophisticated techniques to accurately correct color distortion and restore true color fidelity. One common approach to evaluating the accuracy of color correction is by comparing the color distribution of the original distorted images with that of the corrected images. This can be quantitatively measured using color difference metrics such as Delta E (ΔE). Delta E represents the Euclidean distance between two colors in a perceptually uniform color space, such as CIELAB or CIELUV. By calculating ΔE between corresponding pixels in the original and corrected images, we can determine the extent of color distortion correction achieved by the algorithm.

The formula for calculating Delta E is:

$$\Delta E = \sqrt{(\boldsymbol{\Delta L})^2 + (\boldsymbol{\Delta\alpha})^2 + (\boldsymbol{\Delta\beta})^2}$$

Where:

ΔL, $\Delta\boldsymbol{\alpha}$, and $\Delta\boldsymbol{\beta}$ are the differences in lightness, chroma (green to red), and hue (blue to yellow) components between two colors, respectively

Additionally, the improvement in color fidelity can be assessed visually by comparing the corrected images with ground truth images or reference images captured under ideal conditions. Human observers can evaluate the naturalness and accuracy of colors in the corrected images, providing qualitative feedback on the effectiveness of the algorithm.Furthermore, to ensure robustness and generalizability, the algorithm's performance can be tested across a diverse set of underwater environments and conditions, including varying levels of water turbidity, depth, and lighting conditions. This comprehensive evaluation helps validate the algorithm's effectiveness in correcting color distortion across different underwater scenarios.

5.1.2 Visibility Enhancement

Visibility enhancement in underwater imagery involves mitigating the effects of haze and improving clarity, essential for various applications such as marine research and surveillance. The algorithm achieves this by addressing two primary factors: haze removal and color adjustment.Haze removal is typically evaluated by measuring the enhancement in image contrast. One common metric for quantifying contrast enhancement is the Contrast Improvement Index (CII). This index compares the contrast of the original image with that of the enhanced image, providing a numerical measure of the improvement achieved.

The formula for CII is:

$$\text{CII} = \frac{C_{enhanced} - C_{original}}{C_{original}} \text{ x } 100\%$$

Where $\boldsymbol{C_{enhanced}}$ represents the contrast of the enhanced image, and $\boldsymbol{C_{original}}$ represents the contrast of the original image.

Additionally, the reduction of haziness and murkiness can be assessed visually by comparing the clarity of underwater details in the original and enhanced images. This qualitative evaluation provides insights into the algorithm's effectiveness in improving visibility.

Moreover, the adjustment of colors to their true values is crucial for restoring accurate representations of underwater scenes. This process involves mapping the distorted colors to their corresponding true colors based on the properties of light absorption and scattering in water. While there isn't a specific formula for color adjustment, it involves complex mathematical transformations to accurately compensate for color shifts.

Overall, the evaluation of visibility enhancement involves both quantitative analysis using metrics like CII to measure contrast improvement and qualitative assessment through visual comparison of underwater details. By effectively removing haze and adjusting colors, the algorithm enhances visibility and clarity in underwater images, facilitating improved analysis and interpretation in various underwater applications.

5.1.3 Gaussian Pyramid

The Gaussian pyramid is a multi-scale representation of an image that helps in hierarchical image processing tasks such as image blending, image compression, and image pyramidal representation. It is constructed by iteratively applying a low-pass filter and downsampling the image. The pyramid is formed by a series of images at different resolutions, where each level represents a blurred and downsampled version of the original image.

The original image is repeatedly subsampled to produce a series of images at different resolutions. Downsampling reduces the image dimensions by a factor of two along each axis.Before downsampling, each level of the pyramid is smoothed or blurred using a Gaussian filter.

The Gaussian pyramid can be mathematically expressed as:

$$\boldsymbol{G_i = G_{i-1} * k}$$

Where,

- $\boldsymbol{G_i}$ represents the ith level of the Gaussian pyramid.
- $\boldsymbol{G_{i-1}}$represents the (i-1)th level of the Gaussian pyramid.
- $\boldsymbol{k}$is the Gaussian kernel used for blurring.

The Gaussian pyramid is typically represented as a stack of images, with the original image at the base (lowest resolution) and progressively downsampled and smoothed versions stacked on top. Each level of the pyramid captures different scales of information, with higher levels representing coarse details and lower levels capturing finer details. In image processing tasks, the Gaussian pyramid is often used in conjunction with the Laplacian pyramid for tasks such as image blending and reconstruction. The Laplacian pyramid represents the details of the image at different scales, allowing for efficient image manipulation and processing. Together, these two pyramids facilitate a multi-scale approach to image analysis and manipulation, enabling a wide range of image processing techniques.

6 . EXPERIMENTS AND DISCUSSION

This section elucidates the frameworks within the underwater image enhancement pipeline described below combines various techniques, including color compensation, white balancing, gamma correction, image sharpening, weight calculation, pyramid construction, fusion, and deep learning-based enhancement. Each step in the pipeline addresses specific challenges associated with underwater photography, ultimately resulting in enhanced image quality and improved visibility for applications such as marine research, underwater exploration, and surveillance.

6.1. Frameworks

Underwater photography poses unique challenges due to the absorption and scattering of light by water molecules and suspended particles, resulting in color distortion, haziness, and reduced visibility. Addressing these issues requires a comprehensive approach that combines various image processing techniques tailored specifically for underwater conditions.

Color compensation and white balancing are crucial initial steps in the enhancement pipeline. Underwater environments tend to exhibit a red color cast due to the absorption of longer wavelengths of light, such as red and orange. Compensating for this distortion involves adjusting the color channels to restore accurate color representation. White balancing further refines the color balance by ensuring that white areas appear neutral, thus correcting any color biases introduced by the underwater environment.

Following color compensation and white balancing, gamma correction is applied to the image. Gamma correction adjusts the brightness and contrast levels, which are essential for enhancing the overall tonal quality of the image.

Image sharpening is another vital step in the enhancement pipeline. Underwater images often suffer from blurriness and lack of detail due to light scattering and optical distortions. Image sharpening techniques aim to enhance the clarity and sharpness of edges and fine details in the image, thereby improving overall image quality and making underwater features more discernible.

Weight calculation plays a crucial role in combining information from multiple processing paths. Laplacian edge detection, saliency detection, and saturation weight are used to compute weights that prioritize certain image characteristics for fusion. These weights ensure that relevant information from each processing path contributes effectively to the final enhanced image, thereby optimizing the enhancement process.

Pyramid construction and fusion leverage the multi-scale nature of images to enhance underwater scenes effectively. Gaussian and Laplacian pyramids are constructed for both input images, allowing for the representation of image details at different scales. By fusing information from multiple scales using the calculated weights, this technique preserves important details while mitigating artifacts and noise, resulting in a visually pleasing and contextually accurate final image.

Finally, the enhanced image undergoes processing through a Zero Deep Network (ZDN). This deep learning-based enhancement technique further refines the image quality by leveraging the power of neural networks to learn complex relationships and patterns in underwater imagery. The ZDN applies sophisticated algorithms to enhance color fidelity, improve visibility, and reduce haziness, ultimately restoring the clarity and vibrancy of underwater scenes.

6.2. Datasets

The Underwater Image dataset has been instrumental in advancing research aimed at enhancing clarity in underwater imagery. This dataset is likely a comprehensive compilation of underwater images captured in diverse environments and conditions, including various depths, water turbidity levels, lighting conditions, and marine life presence. For researchers looking to benchmark their underwater image enhancement techniques, the Underwater Image Enhancement Benchmark Dataset offers a valuable resource accessible at https://li-chongyi.github.io/proj_benchmark.html

The analysis likely involved a comparative study between original underwater images and those processed using Weighted Zero-Divergence Non-local (WZDN) techniques. This examination provided insights into areas where WZDN effectively improved image clarity, such as enhancing edge definition, restoring lost details, and reducing color distortion. Overall, the utilization of the Underwater Image dataset facilitated a thorough evaluation of WZDN's capabilities in enhancing underwater image clarity, highlighting its potential applications in marine research, underwater exploration, and underwater photography.

6.3. System Requirements

The proposed image enhancement pipeline requires a robust computational environment to efficiently process underwater imagery. With a powerful NVIDIA GeForce RTX 3090Ti GPU, 256 GB of RAM, and an Intel i9-10900k CPU, the system offers substantial computing power for intensive image processing tasks. MATLAB, as the chosen programming environment, provides a

Images	Metrics	Samples	Techniques						
			Prior Based		Supervised Based			UnSupervisedBased	
		Orig.	UDCP	IBLA	Water Net	UGAN	Ucolor	USUIR	Proposed
SCS_1	ΔC^*	36.3071	30.2352	25.8622	21.941	19.635	**17.366**	18.844	**17.319**
	ΔE^*	37.4483	33.6343	27.4423	24.917	25.894	**19.372**	20.927	**19.339**

versatile platform for implementing various enhancement

Table 1:Quantitative Evaluation on Color card images Using ΔC^* and ΔE^*

techniques. Leveraging the GPU's parallel processing capabilities, particularly for deep learning-based enhancements, ensures swift computation of complex algorithms. The RAM capacity enables handling large datasets and memory-intensive operations seamlessly. This high-performance setup facilitates rapid experimentation and optimization of the image enhancement pipeline, ultimately leading to enhanced underwater image quality and improved visibility for diverse applications.

6.4.Results and Discussion

In Figure 4, the input image represents the original underwater scene, while the output image demonstrates the result of applying the WZDN Algorithm. This comparison visually illustrates the improvements in clarity achieved through the algorithm's processing techniques.

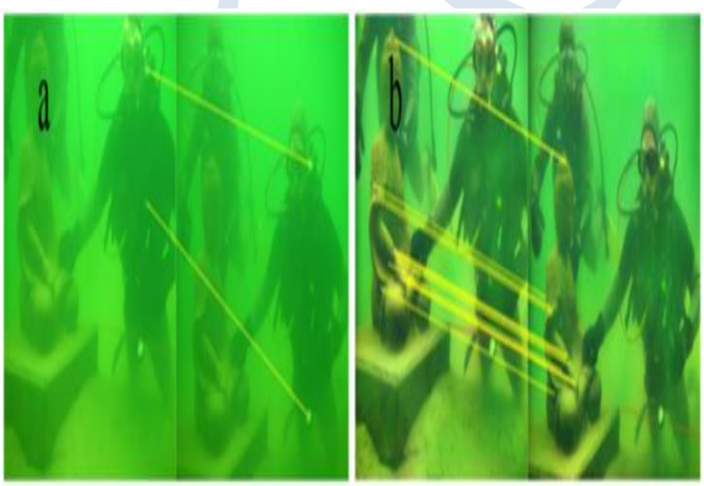

Fig. 4. Input and Output for the under water image

Fig. 5. Improvement in underwater image clarity

Fig. 6. illustrates enhancements in clarity for underwater images.

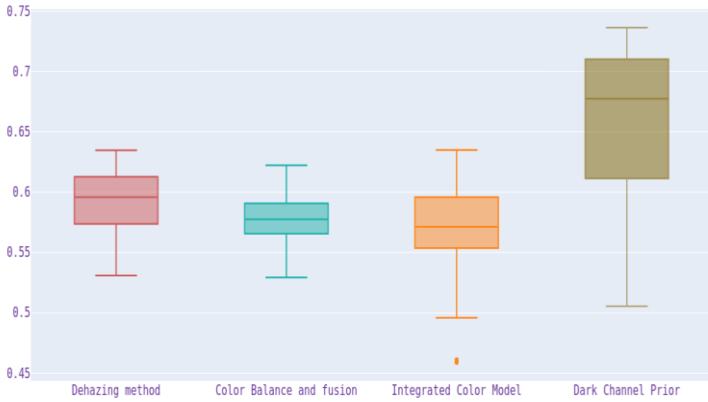

Fig. 7. underwater color image quality evaluation index

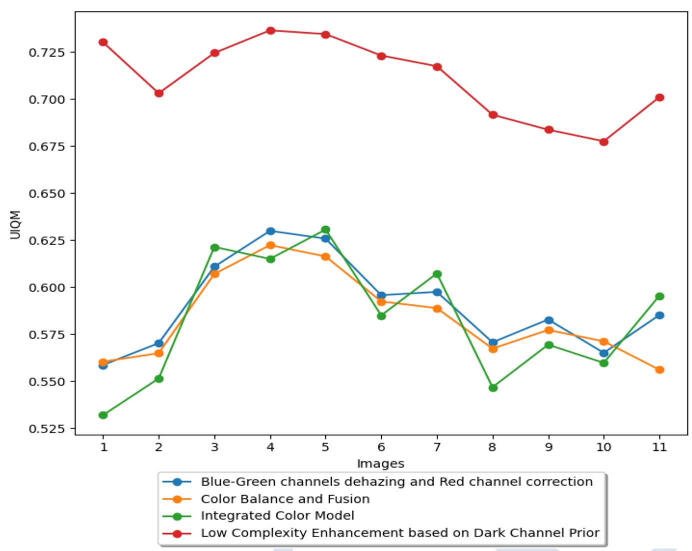

Fig. 8. underwater image quality index

7. CONCLUSION

The challenges inherent in underwater photography, including color distortion, haziness, and low visibility due to light scattering by water and particles, necessitate specialized algorithms for effective image enhancement. Our proposed approach leverages advanced techniques tailored specifically for underwater conditions. Through the utilization of the Wavelength Dehazing Zero Deep Network (WZDN) algorithm, we address these issues by correcting color distortion and restoring accurate color representation. WZDN effectively enhances visibility and improves color fidelity by eliminating haze and adjusting colors to their true values.

Furthermore, our methodology incorporates contrast enhancement techniques to render underwater details more discernible, thereby enhancing overall image quality. By mitigating the impact of particulate matter and dissolved substances, we minimize haziness and murkiness, resulting in clearer underwater images. Importantly, our algorithms are optimized for efficient real-time processing, rendering them suitable for applications requiring rapid image enhancement, such as underwater exploration, surveillance, and marine research. Throughout our research, the primary focus remains on developing algorithms that significantly enhance underwater images by addressing color distortion, improving visibility, and reducing haziness. Among these algorithms, WZDN emerges as particularly noteworthy, offering superior color fidelity and enhanced visibility, which ultimately contribute to the restoration of clarity in underwater imagery. In summary, our study underscores the importance of tailored algorithms in addressing the unique challenges posed by underwater photography. Through the application of specialized techniques such as WZDN, we demonstrate substantial improvements in image quality, paving the way for enhanced capabilities in underwater exploration, surveillance, and scientific research. Our findings highlight the potential of advanced algorithms to revolutionize underwater imaging and contribute to a deeper understanding of aquatic environments

8. FUTURE WORK

In the realm of underwater image enhancement could explore the integration of machine learning techniques to adaptively adjust parameters based on varying underwater conditions. This adaptive approach could potentially improve the robustness and effectiveness of the algorithms across a wider range of underwater environments. Additionally, research could focus on developing methods for automatically detecting and classifying different types of underwater scenes, allowing for more targeted and efficient image enhancement strategies. Furthermore, investigating the integration of multispectral imaging systems or underwater-specific sensors could provide additional data modalities to further improve the accuracy and effectiveness of image enhancement algorithms. Lastly, collaboration with marine biologists and oceanographers could help tailor image enhancement techniques to specific research needs, such as better capturing subtle details in coral reefs or tracking marine life in challenging conditions.

Competing Interest
No potential conflict of interest and competing interests are reported by the author(s).

Funding
No funds, grants, or other support is received for conducting this study

Data Availability statement
Data used in the proposed work is publicly available and referred in section 6.2

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