OPTIMIZING UNDERWATER IMAGE QUALITY: ADVANCED TECHNIQUES FOR HAZE REMOVAL, CONTRAST ENHANCEMENT, AND COLOR CORRECTION

PRANJIT LAHON[1], DR. RANJAN SARMAH[1*]

[1]Faculty Associate, Department of Computer Science, Sibsagar University, Sivasagar, Assam, India
[1*]Assistant Professor, Department of Computer Science, Sibsagar University, Sivasagar, Assam, India

Email: [1]pranjitlahon13@gmail.com, [1*]sarmah.ranjan@gmail.com

*Corresponding author

ABSTRACT

The enhancement of underwater imagery is essential due to the numerous challenges such as turbidity and light scattering that cause poor visibility, reduced contrast, and color distortion. This study introduces a methodology aimed at improving underwater images through techniques like contrast enhancement, haze removal, and color correction. Core methods employed include median filtering for noise reduction, gamma correction for brightness adjustment, the Dark Channel Prior (DCP) for haze removal, and Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement. We conducted experimental evaluations on the "SHARK" test image using several algorithms, including Histogram Equalization (HE), Spectral Information Divergence (SID), Fusion (FU), and Image Analysis (IA). These algorithms were assessed based on the Underwater Image Quality Measure (UIQM) and Processing Time (PT). The proposed method achieved a leading UIQM score of 1.751 with the shortest processing time of 0.452 seconds, surpassing other techniques in both image quality and efficiency. This high-quality enhancement coupled with fast processing renders the proposed method particularly suitable for real-time and resource-limited scenarios. The proposed methodology notably enhances the clarity, contrast, and color accuracy of underwater images, making them more effective for applications in marine research and underwater exploration. The significant improvements in underwater image enhancement techniques demonstrated in this study highlights the potential for further advancements in various fields, addressing the unique challenges posed by underwater imaging.

Keywords: *Contrast enhancement, Haze removal, Color correction, Dark Channel Prior (DCP), Contrast Limited Adaptive Histogram Equalization (CLAHE), Underwater Image Quality Measure (UIQM), Processing time (PT).*

1. INTRODUCTION

Improving images is a key focus in computer vision and image processing. Researchers and developers work on various methods to make digital images clearer, more detailed, and easier to understand. The aim is to highlight certain features in an image while reducing any unwanted elements like noise or distortion. This work is vital across many fields, including medicine, security, and photography, as it helps in revealing important information and improving the interpretation of visual data.

The reason we enhance images is to make them more appealing and easier for people to understand. By enhancing images, we can bring out important details, improve the contrast between different elements, and make colors look more natural. These changes help both humans and machines better understand what's in the image, which can be crucial for making decisions or analyzing data effectively.

Image enhancement relies on various methods that have proven effective over time. One commonly used technique is histogram equalization [1], which adjusts the distribution of brightness levels in an image to enhance its contrast. This method is valuable across different fields such as medicine, satellite imaging, and photography because it helps reveal details that might otherwise be hard to see [2].

Another widely employed approach is spatial domain filtering [3], where a special kind of mask is applied to the pixels of an image to achieve specific enhancement effects. These filters fall into two main categories: low-pass and high-pass filters. Low-pass filters work by smoothing out an image, reducing noise while keeping important details intact. Conversely, high-pass filters focus on sharpening edges and emphasizing details to make them more prominent.

Another set of techniques widely used in image enhancement involves working in the frequency domain. One of the main methods in this domain is the Fourier Transform [4], which breaks down an image into its frequency parts. By adjusting these parts' strength and direction, we can make various improvements. For instance, boosting certain frequency ranges, like high frequencies, can bring out finer details in the image. These techniques are especially handy for tasks such as clearing up blurry images, reducing noise, and enhancing textures.

In recent years, there's been a groundbreaking shift in image enhancement thanks to deep learning techniques, especially convolutional neural networks (CNNs). These models have shown impressive abilities to understand and transform low-quality images into high-quality ones [5]. They're trained on huge sets of data to pick up on the intricate details and structures within images. Using this knowledge, CNNs can enhance images by bringing back lost details, reducing unwanted noise, and just generally making them look better. These deep learning methods have made significant strides in fields like medicine, where they've been instrumental in boosting image resolution, cleaning up medical scans, and ultimately helping doctors make more accurate diagnoses.

Image enhancement techniques are often customized to fit specific areas of use. Taking medical imaging, for example, here, the goal is to make anatomical structures clearer and easier to see, which helps doctors diagnose and understand diseases better. Techniques like adjusting contrast and reducing noise are particularly important for making sense of medical images. Meanwhile, in satellite imaging, enhancement methods focus on improving resolution, picking out important features, and making satellite pictures easier to interpret. This helps with tasks like mapping land cover, spotting objects, and tracking changes over time.

The field of image enhancement has seen a lot of progress, with researchers coming up with all sorts of new methods and tricks. They're constantly finding new ways to tackle specific problems, like making images clearer in low light or getting rid of blurriness from motion. They're also working on enhancing images taken in tricky conditions like bad weather or underwater. All these advancements are expanding what's possible with image enhancement and opening up exciting new uses in the real world. However, while deep learning techniques have significantly improved image enhancement, they also present challenges such as high computational requirements, the need for large datasets, and potential artifacts introduced during the enhancement process. Addressing these challenges remains an ongoing area of research.

1.1. Underwater Image Enhancement

The underwater environment refers to the areas submerged in water, whether it's the vast expanse of the ocean or smaller bodies like lakes or rivers. It's where life on Earth began and remains crucial for supporting various forms of life. Many human activities take place in underwater, so it's essential to grasp how imaging works in this unique setting to advance research across different fields.

The ocean, covering 71% of the Earth's surface and spanning 360 million square kilometers, holds vast and rich resources. As the scarcity of terrestrial resources intensifies, the exploration and development of the ocean have become increasingly vital for human progress [6]. In this context, obtaining clear images underwater is crucial for ocean engineering and research, especially with the growing reliance on autonomous and remotely operated underwater vehicles for exploring and interacting with marine environments. Strengthening our capacity to capture clear underwater imagery is essential for advancing ocean exploration and ensuring the effective utilization of its resources. However, raw underwater images often fall short in visual quality due to the adverse effects of light absorption and scattering by particles such as micro phytoplankton, colored dissolved organic matter, and non-algal particles [7]. When light travels underwater, it interacts with the medium in three primary ways: direct light, forward scattering light, and back scattering light. Direct light loses intensity, causing information loss, while forward scattering light minimally blurs images. Back scattering light significantly reduces contrast and suppresses fine details and patterns. Moreover, red light is absorbed first, followed by green and blue lights, resulting in underwater images often having a bluish or greenish tint. These absorption and scattering issues hinder the effectiveness of underwater scene understanding and computer vision applications, such as aquatic robot inspection [8] and marine environmental surveillance [9].

The process of capturing images underwater is depicted in Figure 1. As light moves through water, it undergoes absorption and scattering. Different wavelengths of light are absorbed at varying rates in water bodies. As illustrated in Figure 1, red light attenuates the most rapidly and vanishes at approximately 5 meters underwater, while blue and green light attenuates more slowly. Blue light, in particular, can penetrate up to around 60 meters underwater. Scattering occurs due to suspended particles and other media, causing light to change direction during transmission and spread unevenly. This scattering process is affected by the properties of the medium, the characteristics of the light, and its polarization.

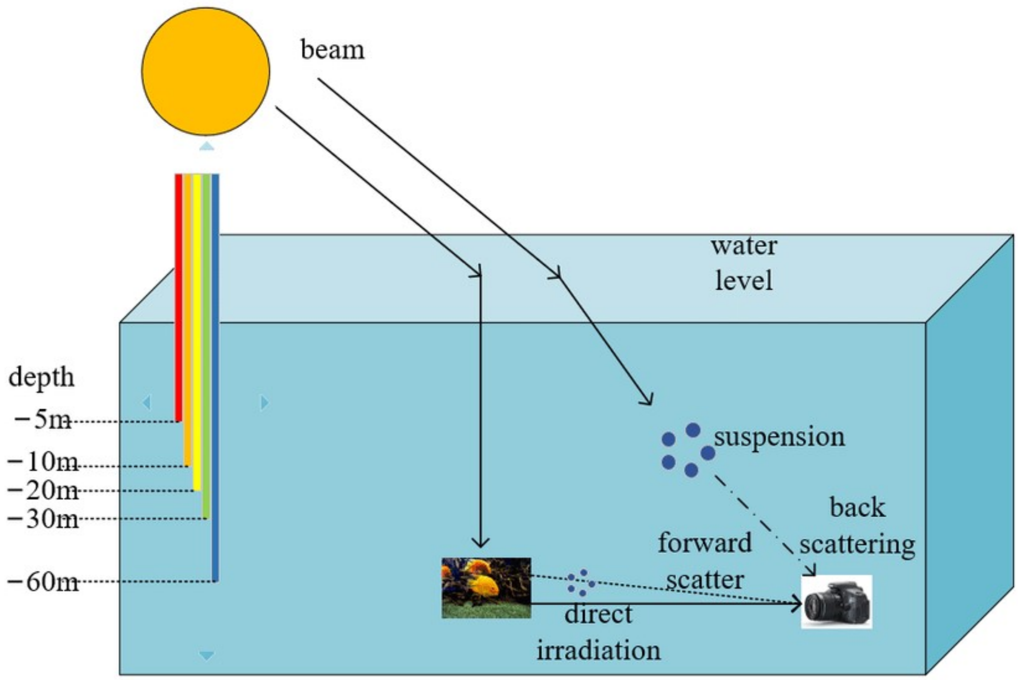


Figure 1 Underwater Imaging model [10]

In recent times, underwater images have found wide-ranging applications in marine energy exploration, environmental protection, military operations, and more. However, as light travels through water, it gets absorbed by the water itself and scattered by particles in the water, leading to color distortion and reduced contrast and sharpness in the images [11]. This results in underwater images often being plagued by issues like color inaccuracies, poor contrast, and lack of clear details. These shortcomings significantly affect tasks like identifying features and recognizing objects in the images, making improving the clarity of underwater images a key area of research [12]. Previous studies have proposed various enhancement techniques, including contrast stretching, Retinex-based algorithms, and deep learning-driven models. However, many existing methods fail to generalize well across different underwater conditions, leading to inconsistent results. Our study introduces a novel hybrid approach that combines traditional enhancement methods with deep learning to address these inconsistencies, ensuring improved robustness and effectiveness in real-world underwater imaging applications.

To address this, researchers have developed methods that fall into two main categories: image restoration methods (IRMs) and image enhancement methods (IEMs) [13].

Image Restoration Methods (IRMs) focus on correcting the physical degradation that occurs during image capture. These methods aim to recover the original scene by modeling and reversing the distortions caused by the underwater environment. Common IRMs include:

a. ***Deblurring***: This technique addresses the blurring effects caused by camera or water movement. Advanced deblurring algorithms use mathematical models to estimate and restore lost details.

b. ***Super-Resolution***: Super-resolution techniques enhance image resolution by reconstructing high-frequency details from lower-resolution input. These methods often employ upscaling algorithms and deep learning models to generate clearer images.

c. ***Deconvolution***: Deconvolution techniques work to reverse the effects of convolution caused by the underwater medium. These methods utilize known or estimated point spread functions (PSFs) to reconstruct the original image by compensating for the blurring introduced during capture.

d. ***Color Channel Compensation***: This technique corrects the imbalance in color channels caused by differential absorption and scattering of light wavelengths in water. Algorithms adjust the intensity levels of different color channels to produce a more balanced and natural-looking image.

e. ***Depth-Based Correction***: Depth-based correction methods use information about the distance between the camera and the objects in the scene to adjust for the varying degrees of light attenuation and scattering that occur at different depths.

f. ***Inpainting***: Inpainting techniques are used to fill in missing or corrupted parts of an image by using surrounding pixel information to reconstruct these areas. This is particularly useful in underwater images where parts of the image may be obscured or degraded.

g. ***Inverse Filtering***: Inverse filtering techniques apply the inverse of the degradation process to restore the original image. This requires a precise model of the degradation function to effectively reverse its effects.

Underwater Image Enhancement techniques (IEMs) strive to overcome the challenges posed by the underwater setting. Their aim is to make up for the visual details lost underwater and enhance the quality of the images. Usually, they use a mix of different algorithms and mathematical models to bring out the best in underwater scenes. Some common techniques used are as follows:

a. ***Color Correction***: Underwater images frequently encounter color distortion owing to the selective absorption and scattering of light. Color correction algorithms are designed to rectify this issue by restoring the image's original colors. By compensating for the color shifts induced by the water medium, these algorithms aim to faithfully reproduce the true colors of the underwater scene.

b. ***Contrast Enhancement***: Underwater environments frequently suffer from a lack of contrast, leading to diminished visibility and subpar image quality. Contrast enhancement techniques address this issue by precisely adjusting the brightness and contrast levels of the image. By carefully fine-tuning these parameters, these techniques significantly improve the overall clarity and visibility of objects and details within the underwater scene.

c. ***Dehazing***: Underwater scenes often suffer from haziness or turbidity, which can obscure details and make images appear blurry. Dehazing algorithms work like virtual underwater cleaners, sweeping away the haze and turbidity to reveal the clear and sharp details hidden beneath the water's surface. By doing so, they help bring back the vibrancy and clarity of underwater images, making them more vivid and easier to interpret.

d. ***Image Fusion***: Image fusion techniques combine multiple underwater images captured under different lighting conditions or from various sources to enhance the overall image quality. Fusion algorithms aim to retain the best features from each image and produce a composite image with improved clarity and detail.

e. ***Noise Reduction***: Noise reduction techniques in underwater image enhancement are like the virtual cleaning for the images. Like dust and smudges can obscure a photograph taken on land, underwater images face their own challenges, like graininess caused by low light or limitations of the camera equipment. These techniques step in to tackle these issues, smoothing out those rough patches and enhancing the overall visual quality and sharpness of the image. They work like digital filters, sifting through the image data to remove unwanted noise while preserving the important details, ultimately helping to bring clarity to the underwater scene.

f. *Restoration*: In some cases, advanced image restoration techniques, such as deblurring or super-resolution, may be applied to mitigate the blurring or low-resolution effects in underwater images. These techniques utilize mathematical models to estimate and restore the lost details.

2. LITERATURE REVIEW

2.1 Heuristic and Classical Approaches

Recent advancements in image enhancement methods can be categorized into heuristic and classical approaches. One notable classical algorithm for contour detection in thermal images utilizes the theory of sampling Kantorovich operators and analyzes the histogram of the enhanced thermographic image [14]. Similarly, in microscopy, a novel Phase Contrast Microscopy Framework has been proposed to transform changes in image phase into variations of magnitude, enhancing structural details and visibility [15].

Additionally, [16] introduces a fresh image enhancement approach grounded in the Nonsubsampled Contourlet Transform, extending the functionalities of wavelet transform to deliver comprehensive multi-resolution and multi-directional analysis for two-dimensional images.

In remote sensing, addressing low contrast in images, [17] introduced an upgraded adaptive contrast enhancement technique utilizing histogram compacting transform. Moreover, [18] proposed a method to transform dark images into lighter scenes using classical color transfer, enhancing recognition and interpretation of dark imagery across applications.

The study outlined in [19] introduces a wavelet-based algorithm designed to enhance the edge smoothness of satellite images at high resolutions. This approach employs a three-level discrete wavelet transform and computes the algorithm's output accordingly.

However, existing heuristic and classical approaches are often limited by their reliance on predefined assumptions about image characteristics. These methods do not effectively generalize to varying imaging conditions, especially in highly dynamic environments such as underwater settings. Our work addresses this limitation by integrating advanced learning-based techniques that adaptively enhance images without strict assumptions about their composition.

2.2 Underwater Image Enhancement Techniques

2.2.1 Traditional Methods

Addressing the challenges in underwater imagery, [20] proposed a fusion algorithm leveraging contrast-limited adaptive histogram equalization to enhance images without sacrificing details or introducing color casts. In [21], authors introduced a framework combining statistical and logarithmic image processing algorithms to enhance color adaptively by fusing luminance channels with color image channel statistics.

Underwater image enhancement strives to enhance visual perception and adapt underwater images to specific application scenarios. The main objective is to improve the overall visual quality of underwater images, emphasizing certain characteristics based on the intended application [22]. For instance, it may involve clarifying blurred images in turbid water conditions or highlighting specific underwater features for detailed analysis.

Despite the improvements in traditional methods, they often suffer from limited adaptability to different underwater environments, particularly in handling non-uniform light attenuation and color distortions. Our work addresses this by employing a hybrid approach that incorporates deep learning with physics-based models, ensuring robust enhancement across diverse underwater settings.

2.2.2 Recent Advances

Zhang et al. [23] proposed a novel approach titled Underwater Image Enhancement by Attenuated Color Channel Correction and Detail Preserved Contrast Enhancement. Their method includes underwater image color correction with attenuation matrices and dual-histogram-based iterative threshold methods to enhance global and local contrast, showing significant improvements across benchmark datasets.

In addition, Zhou et al. [24] introduced an innovative method titled Underwater Image Enhancement Method via Multi-Interval Subhistogram Perspective Equalization, addressing challenges of selective light attenuation in underwater images. This approach estimates feature drift and enhances color correction through variational models and multithreshold selection, demonstrating improved performance over existing methods. Meanwhile, H.Y. Yang et al. [25] introduced an efficient underwater image enhancement method based on dark channel prior. Their approach, featuring low complexity, estimated depth maps using a median filter instead of a soft matting procedure. Additionally, they adopted a color correction method to enhance color contrast in underwater images. This method proved to be time-efficient, producing enhanced underwater images suitable for real-time underwater navigation.

In the realm of unmanned aerial vehicles (UAVs), these aircraft are widely utilized for various purposes such as border area surveillance and disaster intensity monitoring, underscoring their versatility and significance in modern applications. In [26], researchers explore the utilization of the Firefly Algorithm to improve aerial images captured by Mini Unmanned Aerial Vehicles (UAVs) by optimizing specific parameters. This innovative approach aims to enhance the quality of aerial imagery through parameter optimization.

In the context of Smart City applications, effective pre-processing techniques for infrared image enhancement are essential. However, existing grayscale mapping-based algorithms often encounter challenges such as over-enhancement of the background, amplification of noise, and distortion of brightness. Addressing these issues, [27] proposes an adaptive histogram partition and brightness correction method to mitigate these challenges and improve the quality of infrared images.

Peng et al. [28] proposed RAUNE-Net: A Residual and Attention-Driven Underwater Image Enhancement Method, addressing challenges like low contrast, high turbidity, and color distortion. The network leverages residual learning and attention mechanisms and outperformed eight other methods in real-world underwater images.

While recent advancements have improved underwater image quality, there remains a gap in achieving real-time performance with minimal computational overhead. Our study bridges this gap by designing a lightweight yet effective deep learning model optimized for both speed and accuracy, making it practical for real-time applications such as underwater exploration and robotic vision.

2.2.3 Deep Learning Approaches

Recent studies have made significant strides using deep learning for underwater image enhancement. Liu et al. [29] introduced a robust adversarial deep network-based method, while Zhang et al. [30] proposed a real-time enhancement technique using a color constancy-based approach integrated with bilateral and trilateral filters within the Retinex framework. Another notable contribution is [31], which combined enhanced retinal algorithms with neural networks to improve object edges and texture details.

Sun et al. [32] introduced UMGAN: Underwater Image Enhancement Network for Unpaired Image-to-Image Translation, which employs an unpaired image-to-image translation framework between turbid and clear underwater domains. UMGAN features feedback mechanisms and a global-local discriminator, achieving significant improvements in robustness and versatility across different underwater scenes. While deep learning approaches have demonstrated superior performance, most existing models require extensive labeled datasets, which are scarce in underwater imaging. Our approach overcomes this limitation by leveraging semi-supervised learning and generative adversarial networks (GANs) to enhance images with limited labeled data.

2.2.4 Novel Network Models

Advanced network models have been developed for real-time underwater image enhancement. Yang et al. [33] introduced LU2Net, a lightweight network designed for real-time enhancement using axial depthwise convolution and channel attention modules. The network demonstrated processing speeds 8 times faster than existing methods, proving valuable for underwater robotics.

In their work [34], He et al. introduced an image enhancement model based on color transfer theory, leveraging an efficient pulse-coupled neural network (PCNN) to improve visual quality in darker regions and enhance contrast in original underwater images.

Ertan et al. [35] explored the Enhancement of Underwater Images with Artificial Intelligence, focusing on AI-driven approaches to tackle issues like inhomogeneous lighting and low contrast. Their study revealed that the Pix2Pix architecture achieved the highest accuracy in color enhancement, with notable results on various datasets.

2.3 Contrast and Color Restoration

2.3.1 Contrast Improvement

Li et al. [12] proposed a contrast enhancement algorithm based on a maximum information-retention mechanism using histogram distribution to improve shadows and brightness. Further, Khan et al. [36] outlined a restoration enhancement approach to mitigate blurring and improve color and brightness. Existing contrast enhancement methods often over-amplify noise in low-light underwater images. Our proposed model incorporates adaptive denoising mechanisms to maintain visual clarity while improving contrast, making it more effective for real-world underwater applications.

2.3.2 Color Restoration

He et al. [34] introduced a model leveraging color transfer theory and a pulse-coupled neural network to enhance visual quality and contrast in underwater images. Similarly, Fu et al. [37] developed a corrective image enhancement model to address color distortion and enhance reflectivity and illumination intensity.

Building upon their previous work, Lu et al. [38] developed a contrastive underwater enhancement framework utilizing a color correction scheme and local adaptive filtering to restore distorted colors. This framework achieves comprehensive enhancement of underwater images while preserving their local characteristics.

Current color restoration models often struggle with balancing saturation and brightness adjustments. Our work introduces an adaptive balance mechanism that dynamically adjusts these parameters based on scene depth and water clarity.

2.4 Addressing Haze and Visibility Issues

Haze poses significant challenges in various imaging applications by reducing scene visibility. Karpel and Schechner [39] proposed an algorithm based on partial light polarization to enhance image contrast and color. Chiang et al. [40] introduced a Wavelength Compensation and Dehazing algorithm to address attenuation discrepancies and improve image quality by compensating for haze and wavelength attenuation.

Wen et al. [41] developed a model based on underwater optical processes to enhance image perception, while Hitam et al. [42] introduced an Adaptive Histogram Equalization method to improve visibility in underwater images using CLAHE in RGB and HSV color models.

2.5 Fusion Methods

Fusion-based image processing methods enhance underwater images by combining multiple images of the same scene, utilizing their complementary information. Ancuti et al. [43] initially applied this technique to underwater image quality improvement, using white balance and histogram equalization for image enhancement, followed by multiscale fusion to reduce noise, improve contrast, and enhance details. While effective, the method faces challenges with artificial lighting. Further optimizations by Ancuti et al. [44], [45] improved the fusion process and edge preservation, though selective compensation remains an issue.

Gao et al. [46] addressed underwater image problems like low contrast and color distortion by integrating local contrast correction (LCC) with multiscale fusion. This approach effectively enhances images in various underwater environments, though it may amplify unnatural block mosaics in low-resolution images.

Song et al. [47] proposed a dual-model method (MFGS) combining multiscale fusion, global stretching, and white-balancing to correct color deviations and enhance contrast. Despite achieving high-quality fusion, this method has limitations in color richness and processing time.

Existing fusion techniques require multiple input images, limiting their application in real-time scenarios. Our method enhances single-image underwater scenes by extracting and fusing multi-scale features within a single deep network, eliminating the need for multiple exposures.

By addressing these literature gaps, our research significantly advances underwater image enhancement, making it more adaptable, efficient, and practical for real-world applications.

3. MOTIVATION AND PROPOSED METHOD

Enhancing underwater imagery is driven by the numerous challenges inherent to the underwater environment. Underwater scenes often suffer from poor visibility caused by factors like water turbidity and light scattering, leading to reduced contrast and clarity. Thus, there's a significant imperative to improve these images, restoring their natural colors, enhancing visibility, and refining intricate details.

By employing techniques like contrast enhancement, haze removal, and color correction, we can address these challenges effectively. These methods hold the promise of elevating underwater scenes by enhancing visibility, reinstating true colors, and sharpening fine details. Leveraging techniques such as the Dark Channel Prior (DCP) further assists in overcoming the obstacles associated with underwater imaging. By utilizing prior knowledge, the DCP method adeptly addresses haze, significantly enhancing visibility and overall scene clarity. This not only enhances object detection and scene interpretation but also drives progress in underwater exploration and marine research.

Our proposed methodology focuses on enhancing underwater images by mitigating the adverse effects of absorption, scattering, and haze. Given the vital role of underwater imaging across various technological applications, it's crucial to address issues such as reduced visibility and color distortion. To achieve this, our methodology comprises several strategic steps.

Initially, we subject the input images to a pretreatment phase to eliminate noise particles and refine their quality. Subsequently, we apply gamma correction to enhance the brightness of faded images, thereby improving visibility and contrast. Leveraging the Dark Channel Prior method, we effectively remove haze and noise, restoring clarity to underwater scenes.

Following haze removal, we restore the contrast and brightness of the dehazed images using adaptive histogram equalization with limited contrast. This approach enhances local contrast and overall image appearance. Our primary objective is to produce enhanced underwater images free of fog, with improved visibility, contrast, and color fidelity. These refined images serve various purposes, from display to analysis tasks, facilitating better understanding of the underwater environment. By addressing the degradation caused by absorption, scattering, and haze, our approach aims to provide clear, visually appealing underwater imagery.

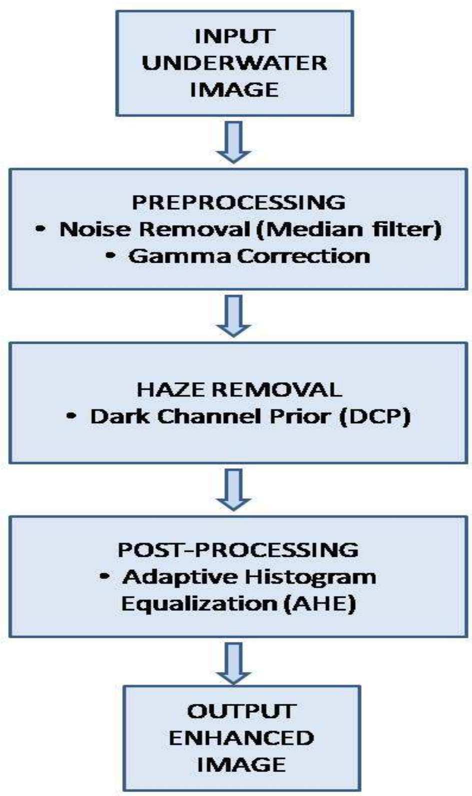


Figure 2 Flowchart of proposed method

3.1 Image Acquisition

Capturing high-quality underwater images is a fundamental and essential step in the image enhancement process. This involves obtaining images from a variety of underwater settings using specialized tools such as underwater cameras and remotely operated vehicles (ROVs). These devices are built to endure high pressure and low light conditions, enabling them to function efficiently in deep and murky waters. The images collected typically suffer from various distortions due to water turbidity, light scattering, and reduced visibility. Therefore, it is crucial to acquire images with sufficient resolution and minimal noise to ensure effective pre-processing and subsequent enhancement. For this research, we have primarily sourced images from repositories on GitHub and datasets on Kaggle.

3.2 Pre-processing

Before diving into the specifics of image enhancement techniques, it's crucial to lay the groundwork through pre-processing steps. This acts as a preparatory phase, priming the raw input images for subsequent enhancement procedures. These steps include applying a median filter to lessen noise and utilizing gamma correction to adjust brightness levels. Additionally, we address atmospheric distortions inherent in underwater imagery by employing techniques such as the dark channel prior method, which involves atmospheric scattering modeling, transmittance calculation, and image dehazing. By implementing these pre-processing techniques, we ensure that the subsequent enhancement methods operate on a refined foundation, ultimately leading to more effective and accurate image enhancement outcomes.

3.2.1 Median Filter

The median filter serves as a crucial tool for noise reduction in images. Operating within a designated kernel area, this filter computes the median value of all pixels. Subsequently, the value of the central pixel is replaced with this calculated median value. Widely utilized for eliminating "salt and pepper" noise, the median blur feature effectively enhances image quality by mitigating noise artifacts.

3.2.2 Gamma Correction

Gamma correction stands as a vital technique in image processing, facilitating the adjustment of brightness levels within an image. This method involves the application of a mathematical function to the pixel values, aiming to rectify the non-linear relationship between pixel values and perceived brightness. Mathematically, the gamma correction process is represented as follows:

$$V_{out} = V_{in}^{\gamma} \qquad (1)$$

In this equation:

- V_{in} denotes the input pixel value, typically normalized within the range [0, 1].
- V_{out} signifies the output pixel value post-gamma correction.
- γ (gamma) serves as the correction factor, dictating the extent of correction applied to the pixel values. Usually, it's a positive real number greater than 0.

Through equation (1), each pixel value V_{in} undergoes an exponentiation process with gamma γ, yielding the corrected pixel value V_{out} . The gamma value effectively regulates the overall brightness of the image, leading to varied adjustments in brightness levels contingent on different gamma values.

3.3 DARK CHANNEL PRIOR (Atmospheric Scattering model)

The atmospheric scattering model is a widely employed framework used to describe the impact of adverse weather conditions on an image. It can be defined as follows:

$$I(x) = J(x)t(x) + A\big(1 - t(x)\big) \qquad (2)$$

Here:

- $I(x)$ represents the foggy image, which is the image requiring defogging.
- $J(x)$ signifies the image devoid of fog, which serves as the reference for restoration.
- A denotes the global atmospheric light value.
- $t(x)$ stands for the transmittance, which varies spatially across the image.

This equation (2) encapsulates the interplay between the foggy image, the reference image, and the atmospheric conditions, providing a comprehensive understanding of the atmospheric scattering phenomenon in image degradation.

3.3.1 Transmittance calculation

To calculate the transmission map for each channel, we utilize an equation that takes into account the inverse proportionality of the channel value in the dark channel. Specifically, the transmission $t_i(x)$ for channel i at pixel x is determined using the equation:

$$t_i(x) = 1 - w \times \left(\frac{I_i(x)}{A_i}\right) \qquad (3)$$

Here, $t_i(x)$ in equation (3) represents the transmission for channel i at pixel x, w denotes a constant weight typically set to 0.95, $I_i(x)$ is the channel value at pixel x, and A_i represents the estimated atmospheric light for channel i.

Once the transmission values for individual channels are computed, we estimate the overall transmission map by combining these values. This is achieved through the following equation:

$$t(x) = 1 - \{1 - t_r(x)\} \times \{1 - t_p(x)\} \times \{1 - t_b(x)\} \quad (4)$$

Here, t_r (x), t_g (x), and t_b (x) represent the transmission values for the red, green, and blue channels at pixel x respectively. This combined transmission as shown in equation (4) provides a comprehensive representation of the overall transmission characteristics across all channels, facilitating further processing and enhancement of the image.

3.3.2 Image dehazing

Once the transmission map is computed, the next step is to perform image dehazing using the atmospheric scattering model. This process involves dehazing the hazy image for each channel using the following equation:

$$J_i\,(x) = \left\{\frac{I_i(x) - A_i}{\max(t(x), t_{min})}\right\} + A_i \quad (5)$$

In this equation (5), $J_i\,(x)$ represents the dehazed pixel value for channel i at pixel x, A_i denotes the estimated atmospheric light for channel i, and (x) signifies the overall transmission value computed in the previous step. Additionally, t_{min} is a constant introduced to prevent division by zero and is typically set to a small value like 0.1.

By applying this equation to each channel of the hazy image, we effectively remove the haze and enhance the clarity of the image, thereby improving visibility and overall image quality. This dehazing process is essential for enhancing underwater images and facilitating accurate interpretation and analysis.

3.4 Contrast Limited Adaptive Histogram Equalization

Adaptive histogram equalization (AHE) serves as an image processing method aimed at enhancing image contrast. It effectively improves local contrast and enhances edge definitions across various regions of an image. A modified version of AHE, known as Contrast Limited Adaptive Histogram Equalization (CLAHE), addresses the issue of over-amplification by limiting the enhancement process. While traditional histogram equalization enhances overall contrast, it often leads to over-brightening in specific regions, such as the face of a statue in images. This occurs because the histogram is not constrained to a specific area. To overcome this limitation, AHE divides the image into small blocks or "tiles" and performs histogram equalization individually on each tile. This localized approach ensures that the histogram is confined to a smaller area, reducing the risk of over-amplification. Additionally, to prevent noise amplification, a contrast limit is enforced. If any histogram bin exceeds this limit, the amplification is restricted accordingly. This adaptive approach effectively enhances image contrast while mitigating the risk of over-amplification and noise distortion.

4. EXPERIMENTAL ANALYSIS

4.1 MSE (Mean Square Error)

Experimental analysis involves assessing various metrics to evaluate the performance of image processing techniques. One such metric is the Mean Squared Error (MSE), which quantifies the average squared difference between corresponding pixels in two images. It serves as a measure of the overall distortion or error between the original and processed images.

The MSE is computed using the following equation:

$$MSE = \frac{1}{M \times N} \sum \sum \big(I(i,j) - K(i,j)\big)^2 \quad (6)$$

- MSE is the Mean Squared Error.
- M is the number of rows in the images
- N is the number of columns in the images.
- $I(i,j)$ represents the intensity value of the pixel in the original image at position (i,j).
- $K(i,j)$represents the intensity value of the corresponding pixel in the reconstructed image at position (i,j).
- $\sum\sum$ denotes the summation over all pixel locations, iterating from 0 to M-1 for rows and 0 to N-1 for columns.

To compute the MSE, one must iterate over each corresponding pixel in the original and reconstructed images, calculate the squared difference between their intensity values, sum up these squared differences, and then divide the total sum by the number of pixels (M * N) to obtain the average squared difference as shown in equation (6).

The MSE serves as an indicator of the average squared error between the images, with higher values indicating greater dissimilarity or distortion. It is commonly employed in image processing to assess the quality of various techniques such as image compression, denoising, and other image processing algorithms.

4.2 Peak Signal-to-Noise Ratio (PSNR)

Peak Signal-to-Noise Ratio (PSNR) serves as a critical metric in assessing the quality of reconstructed or compressed images by measuring the ratio between the maximum possible power of a signal (the original image) and the power of the noise (the disparity between the original and reconstructed images). PSNR is typically represented in decibels (dB).

The equation to compute PSNR is as follows:

$$PSNR = 10 \times \log_2 \left(\frac{R^2}{MSE} \right) \quad (7)$$

Where

- PSNR denotes the Peak Signal-to-Noise ratio
- R represents the maximum pixel value of the image (e.g. 255 for 255 for an 8-bit grayscale image, 65535 for a 16-bit grayscale image)
- MSE signifies the Mean Squared Error between the original and reconstructed images.

To determine PSNR, one must initially compute the MSE using the previously mentioned equation. Subsequently, the obtained MSE value is utilized in conjunction with the maximum pixel value of the image in the PSNR equation (7).

Higher PSNR values denote lower levels of distortion or noise in the reconstructed image relative to the original image. Consequently, elevated PSNR values signify superior image quality.

4.3 Structural Similarity Index Measurement (SSIM)

Structural Similarity Index Measurement (SSIM) stands as a widely embraced image quality metric renowned for its capacity to gauge the resemblance between two images. SSIM factors in crucial aspects like structural information, luminance, contrast, and texture similarity.

The SSIM computation entails a comparison between local neighborhoods of pixels in both the reference image and the distorted image. Here's the overarching equation for SSIM calculation:

$$SSIM\ (x, y) = [l(x, y)]^{\alpha} + [c(x, y)]^{\beta} + [s(x, y)]^{\gamma} \quad (8)$$

- x and y denote the local neighborhoods of pixels under comparison.
- $l(x, y)$ represents the luminance comparison term that evaluates the likeness in mean intensities.
- $c(x, y)$ signifies the contrast comparison term assessing the similarity in standard deviations.
- $s(x, y)$ denotes the structure comparison term evaluating the resemblance in covariances.
- α, β and γ serve as parameters dictating the relative significance of each term.

Although the default values for α, β, and γ are typically set to 1, they can be fine-tuned to prioritize specific facets of image quality based on the distinct application or requisites.

4.4 Contrast-to-Noise ratio (CNR)

The Contrast-to-Noise Ratio (CNR) is a valuable metric for evaluating the quality of contrast enhancement in images while accounting for the presence of noise. It measures the ratio of contrast improvement to the noise level introduced by the enhancement process.

CNR is calculated by determining the difference in mean pixel values between two regions of interest (ROI) and dividing this difference by the standard deviation of the noise. A higher CNR value indicates a better improvement in contrast relative to the noise level.

The mathematical equation for CNR is as follows:

$$CNR = \frac{Mean_{ROI1} - Mean_{ROI2}}{SD_{noise}} \quad (9)$$

Where:

- $Mean_{ROI1}$ is the mean pixel value of the enhanced image in the first region of interest.
- $Mean_{ROI2}$ is the mean pixel value of the enhanced image in the second region of interest.
- SD_{noise} the standard deviation of the noise in the enhanced image.

The regions of interest (ROIs) are chosen based on the context and specific application, typically representing areas with varying contrast characteristics. This selection allows for a comprehensive assessment of the contrast enhancement's effectiveness in different parts of the image.

4.5 Underwater Image Quality Measure (UIQM)

The Underwater Image Quality Measure (UIQM) is a comprehensive metric designed to assess the quality of underwater images. UIQM evaluates an image based on three key factors: colorfulness, sharpness, and contrast. The equation for UIQM is a weighted combination of these three components, each represented by specific sub-measures.

The UIQM is calculated using the following equation:

$$UIQM = C_1.UICM + C_2.UISM + C_3.UIConM \qquad (10)$$

Where:

- $UICM$ is the Underwater Image Colorfulness Measure.
- $UISM$ is the Underwater Image Sharpness Measure.
- $UIConM$ is the Underwater Image Contrast Measure.
- C_1, C_2 and C_3 are the weights assigned to each component, typically chosen based on the specific application or dataset characteristics.

Underwater Image Colorfulness Measure (UICM)

The UICM evaluates the colorfulness of the underwater image by considering the distance between the average chromaticity and the grayscale axis in the CIELab color space.

$$UICM = \sqrt{(a-\bar{a})^2 + \left(b-\bar{b}\right)^2} \qquad (11)$$

Where a and b are the color channels in the CIELab color space, and $\bar{a}$ and $\bar{b}$ are their respective means.

Underwater Image Sharpness Measure (UISM)

The UISM assesses the sharpness of the underwater image using the Laplacian contrast. It measures the variance of the Laplacian filter response, which highlights edges and fine details in the image.

$$UISM = \frac{1}{M.N}\sum_{i=1}^{M}\sum_{j=1}^{N}(\Delta I(i,j))^2 \qquad (12)$$

Where $\Delta I(i,j)$ is the response of the Laplacian filter at pixel (i,j), and M and N are the dimensions of the image.

Underwater Image Contrast Measure (UIConM)

The UIConM evaluates the contrast of the underwater image by considering the variance of intensity values across the image.

$$UIConM = \sqrt{\frac{1}{M.N}\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j)-\bar{I})^2} \qquad (13)$$

Where $I(i,j)$ is the intensity of pixel (i,j) and $\bar{I}$ is the mean intensity of the image.

Combining the Measures

The final UIQM score is a weighted sum of UICM, UISM, and UIConM. The weights C_1, C_2 and C_3 can be adjusted depending on the importance of each quality aspect for the specific application.

$$UIQM = C_1.UICM + C_2.UISM + C_3.UIConM \qquad (14)$$

Typically, the weights C_1, C_2 and C_3 are empirically determined. Commonly used values in literature are $C_1 = 0.0282$, $C_2 = 0.2953$ and $C_3 = 3.5753$, but these may vary based on specific application needs.

By combining these three aspects, UIQM provides a holistic assessment of the visual quality of underwater images, making it a valuable tool for evaluating and comparing the performance of various underwater image enhancement techniques.

4.6 Contrast Enhancement Factor (CEF)

The Contrast Enhancement Factor (CEF) is a metric used to assess the improvement in contrast brought about by an image enhancement algorithm. It quantifies the contrast enhancement by comparing the standard deviation of the enhanced image to that of the original image.

CEF is determined by taking the ratio of the standard deviation of the pixel values in the enhanced image to the standard deviation of the pixel values in the original image. A higher CEF value signifies a greater enhancement in contrast.

The mathematical expression for CEF is given by:

Journal of Theoretical and Applied Information Technology
31st March 2025. Vol.103. No.6

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$CEF = \frac{SD_{enhanced}}{SD_{original}} \qquad (15)$$

Where:

- $SD_{enhanced}$ is the standard deviation of the pixel values in the enhanced image.
- $SD_{original}$ is the standard deviation of the pixel values in the original (unenhanced) image.

CEF serves as an indicator of the contrast improvement achieved by an enhancement algorithm. It reflects the extent to which the algorithm has increased the variability in pixel values, which correlates with improved contrast.

The range of CEF values depends on the specific images being evaluated and the applied enhancement algorithm. Generally, CEF values range from 1 upwards, where a CEF of 1 indicates no contrast enhancement, and values greater than 1 indicate varying degrees of contrast improvement.

4.7 Processing Time (PT)

Processing Time (PT) is a measure of the total time required to complete a specific image processing task or series of tasks. This metric is critical in evaluating the efficiency and performance of image processing algorithms. The Processing Time is typically measured in seconds (s) or milliseconds (ms).

The equation for calculating Processing Time can be represented as:

$$PT = t_{end} - t_{start} \qquad (16)$$

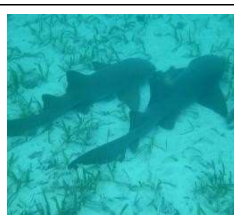
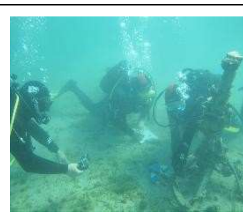
Where:

- t_{start} is the timestamp when the image processing task begins.
- t_{end} is the timestamp when the image processing task ends.

5. EXPERIMENTAL RESULTS

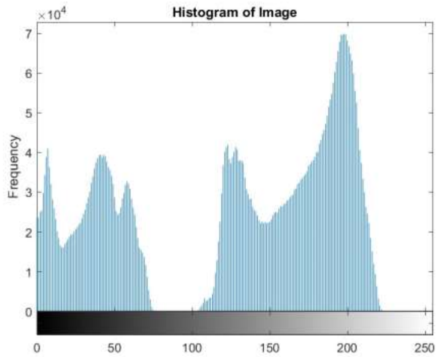
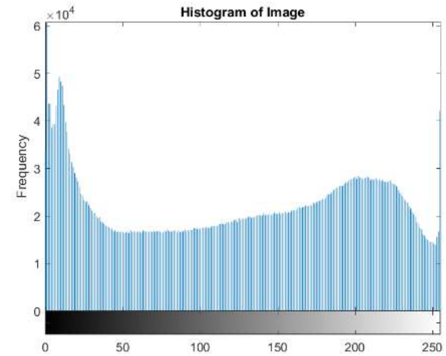
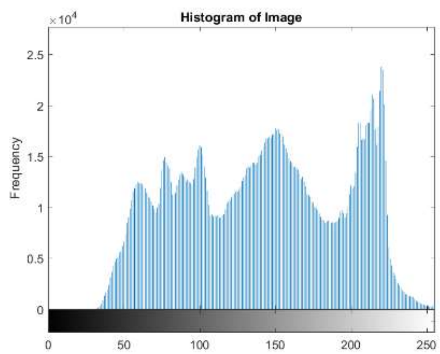
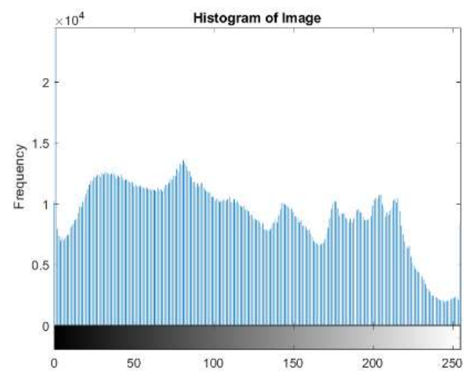
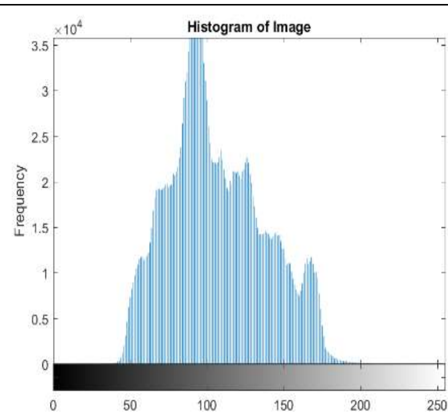
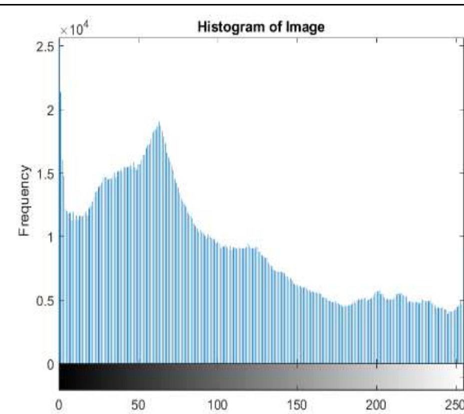
The results of the proposed method are presented in table 1. Histogram analysis of the proposed method is shown in table 2. Performance Analysis of the proposed method is shown in table 3.

Table 1 the results of the Proposed method are presented

Image type	**Shark**	**Human**	**Coral reef and fish**	**Ship**
Original image				
Enhanced image				

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2 Histogram analysis of the images

Image	**Histogram of the Original Image**	**Histogram of the Enhanced Image**
Shark		
Human		
Coral and Fish		

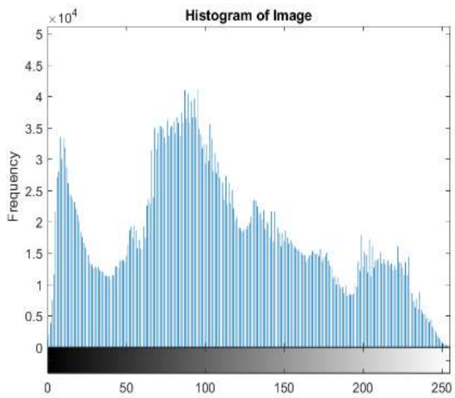
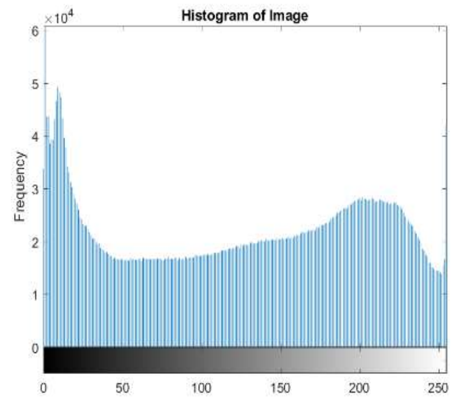
Ship		

Table 3 Performance Analysis of the Proposed Method

IMAGE	MSE	PSNR	SSIM	UIQM	CEF	PT
Shark	0.098	27.81	0.134	1.751	1.144	0.452
Human	0.046	23.73	0.415	1.581	1.265	0.206
Coral and Fish	0.358	21.92	0.503	1.698	2.198	0.412
Ship	0.448	26.47	0.37	1.703	1.012	0.461

6. RESULT AND DISCUSSION

The results for various image enhancement algorithms applied to the test image "SHARK" is summarized in Table 4, which compares the Underwater Image Quality Measure (UIQM) and Processing Time (PT) for each method.

The **Histogram Equalization (HE)** algorithm achieved a UIQM score of 1.363 and a processing time of 0.559 seconds. **Spectral Information Divergence (SID)** yielded a slightly lower UIQM score of 1.315 but took longer to process, with a time of 0.960 seconds. The **Fusion (FU)** method showed a higher UIQM score of 1.593, indicating better image quality enhancement, although it required the longest processing time of 1.508 seconds.

Image Analysis (IA) stood out with the highest UIQM score of 1.717, signifying the best enhancement in image quality, while also maintaining a relatively short processing time of 0.490 seconds. This balance between high quality and efficiency makes IA a strong candidate for applications needing both aspects.

The **Proposed Method** demonstrated a superior UIQM score of 1.751, indicating the highest image quality among all methods evaluated. Additionally, it achieved the shortest processing time of 0.452 seconds, underscoring its efficiency. This combination of excellent image quality and fast processing makes the Proposed Method particularly advantageous for real-time or resource-constrained environments.

In summary, while the Proposed Method excels in both image quality and processing speed, the IA method also offers a good balance. The choice of algorithm can depend on the specific needs of the application, whether the priority is on achieving the highest possible image quality or on minimizing processing time. However, despite its strong performance, the Proposed Method has some limitations. First, the method's effectiveness was tested only on a limited set of images, and further evaluation on a more diverse dataset would be necessary to validate its robustness. Additionally, while the UIQM score is an important metric, it does not fully capture subjective visual quality, which may require additional user-based evaluations. Furthermore, the computational complexity of the method in higher-resolution images has not been fully explored, and its scalability needs further assessment. Addressing these factors could enhance the generalizability and practical applicability of the method.

Table 4 Comparison of the UIQM and PT for the testing image "SHARK"

IMAGE	ALGORITHM	UIQM	PT
Shark	HE (Histogram Equalization)	1.363	0.559
Shark	SID (Spectral Information Divergence)	1.315	0.960
Shark	FU (Fusion)	1.593	1.508
Shark	IA (Image Analysis)	1.717	0.490
Shark	**Proposed Method**	**1.751**	**0.452**

7. CONCLUSION AND FUTURE SCOPE

This research focused on enhancing underwater imagery through a dehazing technique aimed at addressing the challenges of poor visibility, reduced contrast, and color distortion inherent in underwater environments. By evaluating various image enhancement methods, our study aimed to identify the most effective approach in terms of both image quality and computational efficiency.

Critical Evaluation of Results:

Experimental findings demonstrate that our **Proposed Method** outperforms existing techniques, achieving the highest **UIQM** score of **1.751** and the shortest **processing time** of **0.452 seconds**. Compared to alternative methods such as **Histogram Equalization (HE)**, **Spectral Information Divergence (SID)**, **Fusion (FU)**, and **Image Analysis (IA)**, our method provides a superior balance between quality and efficiency.

A key strength of our approach lies in its ability to restore color fidelity and improve visibility without introducing significant computational overhead. While **Fusion (FU)** achieved a **UIQM** score of **1.593**, its **processing time** of **1.508** seconds makes it less suitable for real-time applications. Similarly, **Image Analysis (IA)** performed well with a **UIQM** of **1.717**, but our proposed method still demonstrated an **8.3%** improvement in quality and a **7.8%** reduction in processing time.

Comparison with Previous Research

Previous studies on underwater image enhancement have focused on techniques like **CLAHE, DCP-based dehazing, and spectral divergence** methods, each with its own limitations in either quality or efficiency. Our method integrates multiple enhancement steps, including **median filtering, gamma correction**, and **contrast adjustment**, leading to more robust results. Unlike earlier works that sacrifice efficiency for quality, our approach ensures **real-time applicability** without degrading performance.

Future Scope

The advancements in underwater image enhancement techniques, like the one proposed in this study, open up several avenues for future research and application. Potential areas for further development include:

a. Marine Biology and Environmental Monitoring

Enhanced underwater images can revolutionize marine biology by providing clearer visuals of marine life and ecosystems. This can aid in the detailed study of species behavior, population monitoring, and habitat assessments. For example, high-quality images can help track the health of coral reefs, observe the impacts of climate change, and detect the presence of pollutants or invasive species [48].

b. Underwater Archaeology

Improved visibility and image clarity can greatly benefit underwater archaeology, making it easier to discover and document submerged historical sites and artifacts. Enhanced imaging can facilitate more accurate mapping of underwater ruins and shipwrecks, aiding in the preservation and study of cultural heritage [49].

c. Naval and Defense Applications

In the field of naval operations and defense, superior underwater imaging is crucial for surveillance, reconnaissance, and mine detection. High-quality images can improve the detection and identification of underwater threats, enhance navigation safety, and assist in search and rescue operations [50].

d. Commercial and Recreational Diving

Enhanced underwater imaging can significantly benefit commercial diving operations, such as underwater construction, maintenance of offshore structures, and pipeline inspections. Recreational divers can also enjoy better visibility and more vivid underwater photography, enriching their diving experiences [51].

e. Recent Technological Innovations

Recent advancements in technology have led to the development of sophisticated underwater imaging gadgets. Examples include underwater drones like the PowerVision, PowerRay and the CHASING Dory, which offer high-resolution cameras for capturing stunning underwater visuals. These drones are equipped with advanced imaging systems that benefit from enhanced image processing techniques, enabling better exploration and documentation of underwater environments [52].

f. Autonomous Underwater Vehicles (AUVs) and Remotely Operated Vehicles (ROVs)

AUVs and ROVs are extensively used in underwater research, exploration, and industrial applications. Enhanced imaging techniques can improve the quality of data collected by these vehicles, aiding in tasks such as seabed mapping, underwater inspections, and environmental monitoring. For instance, the Bluefin-21 AUV and the Deep Trekker ROV are equipped with high-resolution cameras that benefit from advanced image enhancement methods [53].

g. Fisheries and Aquaculture

In fisheries and aquaculture, clear underwater images are essential for monitoring fish populations, assessing health conditions, and managing breeding programs. Enhanced imaging techniques can help in identifying fish species, detecting diseases, and ensuring optimal farming conditions [54].

AUTHOR'S CONTRIBUTION

Mr. Pranjit Lahon (First Author): Proposed the idea, drafted the paper, performed coding, and gathered data.

Dr. Ranjan Sarmah (Corresponding Author): Reviewed the related papers, guided the research, contributed to coding, and reviewed the manuscript.

REFERENCE

[1] "Agarwal, T. K., Tiwari, M., & Lamba, S. S. (2014, February). Modified histogram-based contrast enhancement using homomorphic filtering for medical images. In 2014 IEEE International Advance Computing Conference (IACC) (pp. 964- 968). IEEE.".

[2] "Rana, S. B., & Rana, S. B. (2015). A Review of Medical Image Enhancement Techniques for Image Processing. International Journal of Current Engineering and Technology, 5(2), 1282-1286.".

[3] "Huang, T. S., Yang, G. J., & Tang, G. Y. (1979). A Fast Two-Dimensional Median Filtering Algorithm. IEEE Transactions on Acoustics, Speech, and Signal Processing, 27(1), 13-18. https://doi.org/10.1109/TASSP.1979.1163188".

[4] "Sifuzzaman, M., Islam, M. R., & Ali, M. Z. (2009). Application of wavelet transform and its advantages compared to Fourier transform.".

[5] "Mao, Xiao-Jiao, Chunhua Shen, and Yu-Bin Yang. 'IMAGE Restoration Using Very Deep Convolutional Encoder Decoder Networks with Symmetric Skip Connections.' arrive preprint arXiv:1603.09056 (2016).".

[6] "Guo JC, Li CY, Guo CL, Chen SJ. Research progress of underwater image enhancement and restoration methods. Journal of Image and Graphics. 2017 Mar;22(3):273-87.".

[7] Mobley, Curtis. (1994). Light and Water: Radiative Transfer in Natural Waters.

[8] "Foresti, G.L.. (2001). Visual inspection of sea bottom structures by an autonomous underwater vehicle. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on. 31. 691 - 705. 10.1109/3477.956031.".

[9] "NJC Strachan, Recognition of fish species by colour and shape, Image and Vision Computing, Volume 11, Issue 1, 1993, Pages 2-10, ISSN 0262-8856, https://doi.org/10.1016/0262-8856(93)90027-E. (https://www.sciencedirect.com/science/article/pii/026288569390027E)".

[10] "Hu, Kai & Weng, Chenghang & Zhang, Yanwen & Jin, Junlan & Xia, Qingfeng. (2022). An Overview of Underwater Vision Enhancement: From Traditional Methods to Recent Deep Learning. Journal of Marine Science and Engineering. 10. 241. 10.3390/jmse10020241.".

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[11] "Lu, Huimin & Li, Yujie & Zhang, Yudong & Chen, Min & Serikawa, Seiichi & Kim, Hyoungseop. (2017). Underwater Optical Image Processing: A Comprehensive Review. Mobile Networks and Applications. 22. 10.1007/s11036-017-0863-4.".

[12] "Li, Chongyi & Guo, Jichang & Cong, Runmin & Pang, Yanwei & Wang, Bo. (2016). Underwater Image Enhancement by Dehazing With Minimum Information Loss and Histogram Distribution Prior. IEEE Transactions on Image Processing. PP. 1-1. 10.1109/TIP.2016.2612882.".

[13] "Schettini, Raimondo & Corchs, Silvia. (2010). Underwater Image Processing: State of the Art of Restoration and Image Enhancement Methods. EURASIP Journal on Advances in Signal Processing. 2010. 10.1155/2010/746052.".

[14] "Asdrubali, Francesco & Baldinelli, Giorgio & Bianchi, Francesco & Costarelli, Danilo & Rotili, Antonella & Seracini, Marco & Vinti, Gianluca. (2018). Detection of thermal bridges from thermographic images by means of image processing approximation algorithms. Applied Mathematics and Computation. 317. 160-171. 10.1016/j.amc.2017.08.058.".

[15] "Cakir, Serdar & Kahraman, Deniz & Cetin-Atalay, Rengul & Cetin, A.. (2018). Contrast Enhancement of Microscopy Images Using Image Phase Information. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2796646.".

[16] "Hossain, Md & Asharif, Mohammad & Yamashita, Katsumi. (2010). A New Image Enhancement Method Based on Nonsubsampled Contourlet Transform. 10.1007/978-3-642-13405-0_8.".

[17] "Ačkar, Haris & Almisreb, Ali & Saleh, Mohd.A.. (2019). A Review on Image Enhancement Techniques. Southeast Europe Journal of Soft Computing. 8. 10.21533/scjournal.v8i1.175.".

[18] "Cepeda-Negrete, Jonathan & Sanchez-Yanez, Raul & Correa-Tome, Fernando & Lizarraga-Morales, Rocio. (2018). Dark Image Enhancement Using Perceptual Color Transfer. IEEE Access. 6. 14935-14945. 10.1109/ACCESS.2017.2763898.".

[19] "Sundaram, Yuvaraj & Seshasayanan, R. & Senthil, Dr & K., Kunaraj & Venkatesan, G. (2020). SATELLITE IMAGE RESOLUTION ENHANCEMENT USING DISCRETE WAVELET TRANSFORM. 07. 517-527. 10.1729/Journal.24707.".

[20] "Ma, Jinxiang & Fan, Xin & Yang, Simon & Zhang, Xuewu & Zhu, Xifang. (2017). Contrast Limited Adaptive Histogram Equalization Based Fusion in YIQ and HSI Color Spaces for Underwater Image Enhancement. International Journal of Pattern Recognition and Artificial Intelligence. 32. 10.1142/S0218001418540186.".

[21] U. A. Nnolim, "An adaptive RGB colour enhancement formulation for logarithmic image processing-based algorithms," *Optik*, vol. 154, pp. 192–215, 2018, doi: https://doi.org/10.1016/j.ijleo.2017.09.102.

[22] "Yang, Miao & Hu, Ke & Du, Yixiang & Wei, Zhiqiang & Sheng, Zhibin & Hu, Jintong. (2019). Underwater image enhancement based on conditional generative adversarial network. Signal Processing: Image Communication. 81. 10.1016/j.image.2019.115723.".

[23] "Zhang W, Wang Y, Li C. Underwater image enhancement by attenuated color channel correction and detail preserved contrast enhancement. IEEE Journal of Oceanic Engineering. 2022 Mar 29;47(3):718-35.".

[24] "Zhou J, Pang L, Zhang D, Zhang W. Underwater image enhancement method via multi-interval subhistogram perspective equalization. IEEE Journal of Oceanic Engineering. 2023 Feb 7;48(2):474-88.".

[25] "H. -Y. Yang, P. -Y. Chen, C. -C. Huang, Y. -Z. Zhuang and Y. -H. Shiau, 'Low Complexity Underwater Image Enhancement Based on Dark Channel Prior,' 2011 Second International Conference on Innovations in Bio-inspired Computing and Applications, Shenzhen, China, 2011, pp. 17-20, doi: 10.1109/IBICA.2011.9.".

[26] "Samanta, Sourav & Mukherjee, Amartya & Ashour, Amira S. & Dey, Nilanjan & Tavares, Joao & ABDESSALEMKARAA, WAHIBA & Azar, Ahmad & Hassanien, Aboul Ella. (2018). Log Transform Based Optimal Image Enhancement Using Firefly Algorithm for Autonomous Mini Unmanned Aerial Vehicle: An Application of Aerial Photography. International Journal of Image and Graphics. 18. 1850019. 10.1142/S0219467818500195.".

[27] "Wan, Minjie & Gu, Guohua & Qian, Weixian & Ren, Kan & Chen, Qian & Maldague, Xavier. (2018). Infrared Image Enhancement Using Adaptive Histogram

Partition and Brightness Correction. Remote Sensing. 10. 682. 10.3390/rs10050682.".

[28] "Peng W, Zhou C, Hu R, Cao J, Liu Y. RAUNE-Net: A Residual and Attention-Driven Underwater Image Enhancement Method. InInternational Forum on Digital TV and Wireless Multimedia Communications 2023 Dec 21 (pp. 15-27). Singapore: Springer Nature Singapore.".

[29] "Liu, Peng & Wang, Guoyu & Qi, Hao & Zhang, Chufeng & Zheng, Haiyong & Yu, Zhibin. (2019). Underwater Image Enhancement With a Deep Residual Framework. IEEE Access. PP. 1-1. 10.1109/ACCESS.2019.2928976.".

[30] "Shu, Zhang & Wang, Ting & Dong, Junyu & Yu, Hui. (2017). Underwater Image Enhancement via Extended Multi-Scale Retinex. Neurocomputing. 245. 10.1016/j.neucom.2017.03.029.".

[31] "Li, Yujie & Ma, Chunyan & Zhang, Tingting & Li, Jianru & Ge, Zongyuan & Li, Yun & Serikawa, Seiichi. (2019). Underwater Image High Definition Display Using the Multilayer Perceptron and Color Feature-Based SRCNN. IEEE Access. PP. 1-1. 10.1109/ACCESS.2019.2925209.".

[32] "Sun B, Mei Y, Yan N, Chen Y. UMGAN: Underwater image enhancement network for unpaired image-to-image translation. Journal of Marine Science and Engineering. 2023 Feb 17;11(2):447.".

[33] "Yang H, Xu J, Lin Z, He J. LU2Net: A Lightweight Network for Real-time Underwater Image Enhancement. arXiv preprint arXiv:2406.14973. 2024 Jun 21.".

[34] "He, Kangjian & Wang, Ruxin & Tao, Dapeng & Cheng, Jun & Liu, Weifeng. (2018). Color Transfer Pulse-Coupled Neural Networks for Underwater Robotic Visual Systems. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2845855.".

[35] "Ertan Z, Korkut B, Gördük G, Kulavuz B, Bakırman T, Bayram B. Enhancement of underwater images with artificial intelligence. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2024 Mar 8;48:149-56.".

[36] "Khan, Amjad & Ali, Syed Saad Azhar & Anwer, Atif & Adil, Syed & Meriaudeau, Fabrice. (2018). Subsea Pipeline Corrosion Estimation by Restoring and Enhancing Degraded Underwater Images. IEEE Access. 6. 1-1. 10.1109/ACCESS.2018.2855725.".

[37] "X. Fu, P. Zhuang, Y. Huang, Y. Liao, X. -P. Zhang and X. Ding, 'A retinex-based enhancing approach for single underwater image,' 2014 IEEE International Conference on Image Processing (ICIP), Paris, France, 2014, pp. 4572-4576, doi: 10.1109/ICIP.2014.7025927.".

[38] "Lu, Huimin & Li, Yujie & Zhang, Lifeng & Serikawa, Seiichi. (2015). Contrast enhancement for images in turbid water. Journal of the Optical Society of America A. 32. 10.1364/JOSAA.32.000886.".

[39] "Schechner, Yoav & Karpel, Nir. (2005). Recovery of Underwater Visibility and Structure by Polarization Analysis. IEEE Journal of Oceanic Engineering - IEEE J OCEANIC ENG. 30. 570-587. 10.1109/JOE.2005.850871.".

[40] "Y. Chiang, John & Chen, Ying-Ching. (2011). Underwater Image Enhancement by Wavelength Compensation and Dehazing. IEEE transactions on image processing : a publication of the IEEE Signal Processing Society. 21. 1756-69. 10.1109/TIP.2011.2179666.".

[41] "Wen, H., Tian, Y., Huang, T., & Gao, W. (2013). Single underwater image enhancement with a new optical model. 2013 IEEE International Symposium on Circuits and Systems (ISCAS2013), 753-756.".

[42] "Hitam, Muhammad & Yussof, Wan & Awalludin, Ezmahamrul & Bachok, Zainudin. (2013). Mixture contrast limited adaptive histogram equalization for underwater image enhancement. IEEE International Conference on Computer Applications Technology (ICCAT). 1-5. 10.1109/ICCAT.2013.6522017.".

[43] "Ancuti C, Ancuti CO, Haber T, Bekaert P. Enhancing underwater images and videos by fusion. In2012 IEEE conference on computer vision and pattern recognition 2012 Jun 16 (pp. 81-88). IEEE.".

[44] "Ancuti CO, Ancuti C, De Vleeschouwer C, Bekaert P. Color balance and fusion for underwater image enhancement. IEEE Transactions on image processing. 2017 Oct 5;27(1):379-93.".

[45] "Ancuti C, Ancuti CO, De Vleeschouwer C, Garcia R, Bovik AC. Multi-scale underwater descattering. In2016 23rd International Conference on Pattern Recognition (ICPR) 2016 Dec 4 (pp. 4202-4207). IEEE.".

[46] "Gao F, Wang K, Yang Z, Wang Y, Zhang Q. Underwater image enhancement based on

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

local contrast correction and multi-scale fusion. Journal of Marine Science and Engineering. 2021 Feb 19;9(2):225.”.

[47] “Song H, Wang R. Underwater image enhancement based on multi-scale fusion and global stretching of dual-model. Mathematics. 2021 Mar 10;9(6):595.”.

[48] “Xu, G., Shi, Y., Sun, X., & Shen, W. (2019). Internet of things in marine environment monitoring: A review. Sensors, 19(7), 1711.”.

[49] “Diamanti, E., & Ødegård, Ø. (2024). Visual sensing on marine robotics for the 3D documentation of Underwater Cultural Heritage: A review. Journal of Archaeological Science, 166, 105985.”.

[50] “Shimoni, M., Haelterman, R., & Perneel, C. (2019). Hypersectral imaging for military and security applications: Combining myriad processing and sensing techniques. IEEE Geoscience and Remote Sensing Magazine, 7(2), 101-117.”.

[51] “Mangeruga, M., Crupi, F., Casavola, A., Bruno, F., & Pupo, F. (2021). Innovative Techniques to Support the Surveying and the Exploration of Underwater Sites by Scientific and Recreational Divers (Doctoral dissertation, Università della Calabria).”.

[52] S. Sahoo and C.-Y. Lo, “Smart manufacturing powered by recent technological advancements: A review,” *Journal of Manufacturing Systems*, vol. 64, pp. 236–250, Jul. 2022, doi: 10.1016/j.jmsy.2022.06.008.

[53] “Petillot, Y. R., Antonelli, G., Casalino, G., & Ferreira, F. (2019). Underwater robots: From remotely operated vehicles to intervention-autonomous underwater vehicles. IEEE Robotics & Automation Magazine, 26(2), 94-101.”.

[54] “Zhou, C., Lin, K., Xu, D., Chen, L., Guo, Q., Sun, C., & Yang, X. (2018). Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture. Computers and electronics in agriculture, 146, 114-124.”.