Original Article

Underwater Image Enhancement In Multi-Domain By Enhanced Wavelength Compensation And Image Dehazing

Piyush Bajaj[1*], Er.Shevata Bala[2]

[1*]M-Tech scholar, ECE department UIET lalru, Mani.bajaj92@gmail.com
[2]Assistant professor, Department of Electronicsand communication, UIET. shevetabala@ugichd.edu.in

*Corresponding Author: - Piyush Bajaj
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Abstract

Underwater images usually lack contrast and suffer from color distortion due to light beam scattering and attenuation. Light scattering is due to the presence of suspended particles in water in form of both organic and inorganic material which reflects and deflects the light in an unpredictable manner before it reaches the sensor and results in an image which is low in contrast. Water as a medium readily absorbs light, and moreover different wavelengths of light as absorbs at different rates.. In this era, underwater environment has attained more attention of scholars and scientists to observe the variation in it, due to human influence. In this article, we have proposed a new enhancement technique called Wavelength Compensation and Image Dehazing (WCID) in addition with Wavelet Discrete Transform (WDT). In this proposed technique underwater images are enhanced in frequency as well as in time domain, to boost image quality in both the domains and produce better dehazed throughput. The proposed methodology is implemented over MATLAB platform.

Key words: WCID, DWT, IDWT, AHE, Dehazing.

1-INTRODUCTION:

Similar to light traveling in the air, the underwater light propagation suffers from scattering and absorption. Nonetheless, the magnitude of absorption and scattering is enormous. While the light attenuation coefficients in the air are measured in inverse kilometers for an underwater environment it is in inverse meters. Such severe degradation of light poses serious challenges for imaging sensors to capture the information of the underwater area of interest. Unlike air, water is only transparent to the visible part of the electromagnetic spectrum and opaque to all other wavelengths. Furthermore, the constituent wavelengths of the visible spectrum are absorbed in different rates with longer wavelengths are absorbed more rapidly. The decay of light energy in water is truly remarkable. In the crystal clears waters of the middle oceans less than 1% of light energy remain by the depth of 150m. Hence the visibility degradation is such that the object is harder to see beyond the 20m range and in turbid coastal waters the visibility falls below the 5m mark. Also no natural light from sun reaches below 1km of sea. Hence, the amount of light with in water is always less than the amount of light over the surface of water. Therefore images obtained under water generally have low visual quality.
An underwater image is regarded as a linear combination of these three components. The forward scattering component causes blurred image structures whereas the backward scattering veils image edges and details. Simultaneously, as shown in Fig. 1(b), different wavelengths of light are attenuated at different rates in water. Concretely, the red light first disappears since it has longest wavelength or minimum energy, while the blue and green lights show the opposite case. This property results in the underwater images with bluish or greenish tone [1].

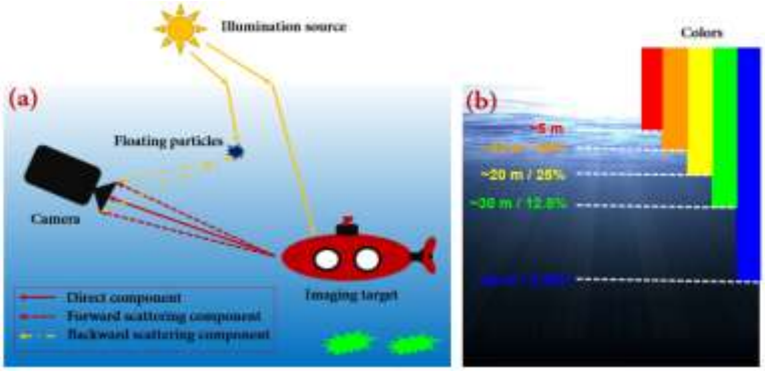


Figure 1.1 Schematic diagrams of (a) underwater imaging model and (b) light Attenuation at different rates in water.

Underwater object tracking is pivotal in applications, such as underwater search and rescue operations, homeland and maritime security, deep ocean exploration, underwater robot navigation, and sea life monitoring. These applications require efficient and accurate vision-based underwater sea analytics, including image enhancement, image quality assessment, and target tracking methods. On the other hand, high noise and low-light situations pose enormous challenges for marine image/video analytics understanding. Further exacerbating these issues are the inherent underwater distortions including absorption and scattering of light causing low contrast, no uniform illumination, diminished colors, and fuzz. This makes computer vision tasks for detection, recognition, and tracking in underwater environments much more challenging than in open-air environments [2].

Studies have included identifying, detecting, analyzing objects, living organisms at the macro, and sometimes micro-levels focusing on a category of topics in recent years. It is known that dynamic light diffusion is a physical method used to determine the distribution of particles in solutions and suspensions. These non-destructive and fast methods are used to determine the particle size in the range of few nanometers to microns. It is also known that the emission wavelength of a medium in question reflects the amount of its deviation. The light emission is also overshadowed by the accumulation of the water particles. Thus, the particles can further increase the deviation of the angle and the orientation of direct motion of light in water [3].

Underwater robotics represents a fast-growing research area. Recently, great efforts are being made in developing autonomous underwater vehicles (AUVs) deployed to tackle challenging engineering problems such as underwater archaeological exploration, garbage collection, underwater rescue operations, ocean floor exploration, and military operations. Many of these applications require real-time interpretation of images/videos for the AUV to intelligently perceive the environment and take follow-up measures. Underwater images that are degraded due to the transmission of light in water could hinder the correct interpretation of the camera input, thereby inhibiting the capability of the vehicle to interact with the environment. Thus, for the above applications, the first step before any downstream task (object recognition, object classification, or object detection) is image enhancement [4].

2-LITRATURE REVIEW:

This chapter presents a comprehensive review of literature focusing on various techniques that are used to enhance under water image and restore visibility and quality of the image. There is a wide variety of technologies as well as techniques used for underwater image restoration and therefore the following discussion categorises and groups them in relation to their distinguishing features.

Peixian Zhuang et. al [5], developed a Bayesian retinex algorithm for enhancing single underwater image with multiorder gradient priors of reflectance and illumination. First, a simple yet effective color correction approach was adopted to remove color casts and recover naturalness. Then a maximum a posteriori formulation for underwater image enhancement was established on the color-corrected image by imposing multiorder gradient priors on reflectance and illumination. Meanwhile, a complex underwater image enhancement issue was turned into two simple denoising sub problems where their convergence analyses were mathematically provided, and their solutions was derived by an efficient optimization algorithm. Besides, the proposed model was fast implemented on pixel wise operations while not requiring additional prior knowledge about underwater imaging conditions Yecai et. al [6], proposed a new multiscale dense generative adversarial network (GAN) for enhancing underwater images. The residual multiscale dense block was presented in the generator, where the multiscale, dense concatenation and residual learning can boost the performance, render more details, and utilize previous features, respectively. And the discriminator employs computationally light spectral normalization to stabilize the training of the discriminator. Meanwhile, non-saturating GAN loss function combining loss and gradient loss was presented to focus on image features of ground truth Jahidul et. al [7], presented a conditional generative adversarial network-based model for real-time underwater image enhancement. To supervise the adversarial training, an objective function that evaluates the perceptual image quality based on its global content, color, local texture, and style information was formulated. Author also presented EUVP, a largescale dataset of a paired and an unpaired collection of underwater images (of ‘poor’ and ‘good’ quality) that were captured using seven different cameras over various visibility conditions during oceanic explorations and human-robot collaborative experiments.

3.1- PROBLEM STATEMENT

This is a general observation that the quality of an image taken with in water is always degraded. It loses the actual tonal quality and the contrast necessary for distinguishing the object of interest present in the image. The situation becomes more challenging when the neighboring objects have very minor differences in pixel intensity values. This situation poses a serious challenge to extract finer details from the data and reduces the performance of the algorithms used to extract information from the images. Therefore, there is a pressing demand for images taken underwater much be processed in such a way that they should represent their true tonal details. Underwater imagery has wide range of applications for example investigation of aquatic life, quality of water, defense and security purposes etc. therefore images or videos obtained for meeting these objectives much carry the exact details.

3.2- MOTIVATION

Software based underwater image enhancement techniques are usually work by controlling some aspect of the mathematical model of underwater to compensate for the degrading effects introduced by the water's light absorption and the presence of organic and inorganic particles in water. Current state of the art method for underwater image restoration are typically designed for a single image input as using multiple images for the processing usually require more computational resources and may not be suitable for the real-time applications. Amongst the single image enhancements method, those based on the image fusion methodologies shows the most promising results [8]

3.3-OBJECTIVES OF RESEARCH

1. To explore the need for optimizing the technique of underwater image enhancement.
2. To optimize the underwater image enhancement technique in frequency domain by combining WCID and wavelet transformation technique.
3. To compare and contrast the performance of proposed method with the existing techniques and methods.

3 .4-PROPOSED RESEARCH:

Underwater Image quality can be improved in the form of contrast, brightness, visibility in low resolution image by using image enhancement technique. A new enhancement technique called Wavelength Compensation and Image Dehazing (WCID) in addition with Wavelet Discrete Transform (WDT) is used here for amplifying the contrast adjustment, color modification and edges concentration. These wavelets contain different data about the image. LL corresponds to low frequency data of smooth region of images like region of less brightness and less contrast. And the other three wavelets contain the high frequency data of the image. The WCID algorithm has been employed for distortion mitigation caused due to light scattering and colour change. Based on depth of image object from the source, segmentation of background and foreground within the image is formulated. The foreground and background light intensities are then compared to determine an artificial light scattering effect is employed during image acquiring process. Flow diagram of proposed technique is depicted below in figure 3.1.

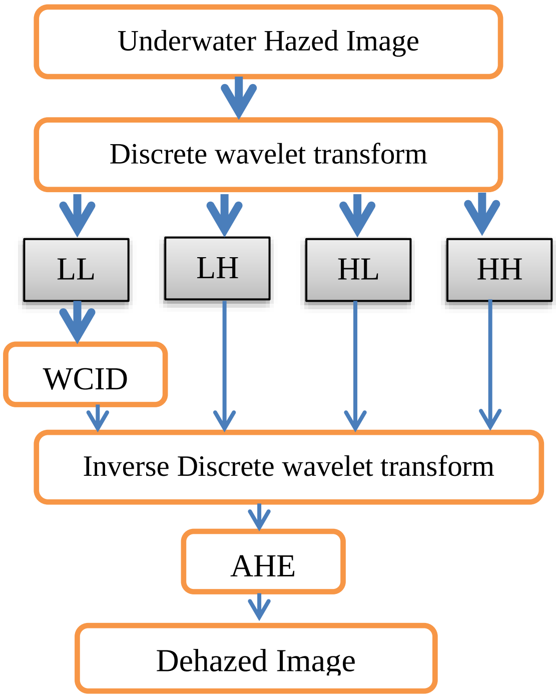


Figure 3.1: Proposed Implementation flow diagram

3.4.1-HAZED IMAGE

Applications using computer vision algorithms require certain degree of input image quality to provide successful results. Some methods are particularly sensitive to artifacts that may appear in images and videos captured in uncontrolled environment such as noise, low contrast, color distortions, or lack of light in the scene.

As it is not possible to assure ideal conditions in all situations, additional processing has to be implemented to mitigate the negative weather conditions in the environment. One of such methods is dehazing, which aims to improve the visibility of images that contain haze or fog. These phenomena are usually present in outdoor scenes where different weather conditions greatly influence the quality of acquired digital images. Dataset used in this article is taken from www.bubblevision.com. Few of the images from the dataset are depicted as under.

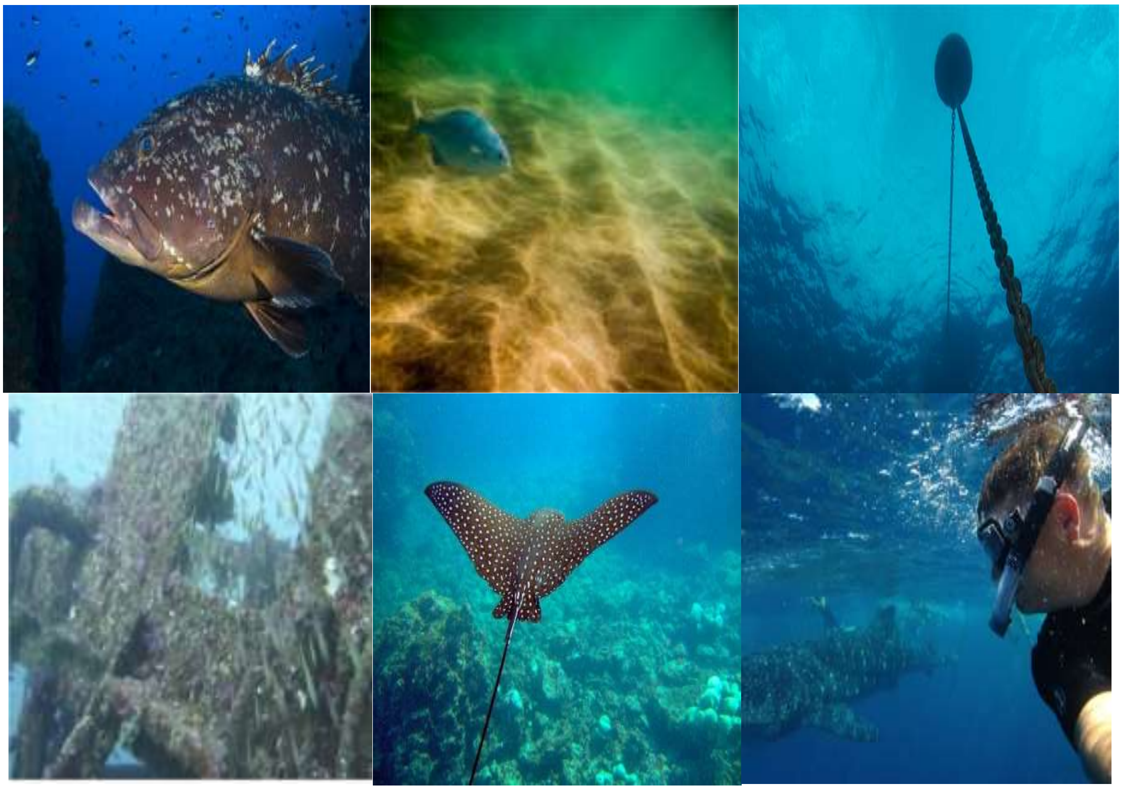


Figure 3.2 Hazed input dataset

3.4.2-DISCRETE WAVELET TRANSFORM

The DWT represents the signal in dynamic sub-band decomposition. Generation of the DWT in a wavelet packet allows sub-band analysis without the constraint of dynamic decomposition. The discrete wavelet packet transform (DWPT) performs an adaptive decomposition of frequency axis. The specific decomposition will be selected according to an optimization criterion.

The Discrete Wavelet Transform (DWT), based on time-scale representation, provides efficient multi-resolution subband decomposition of signals. It has become a powerful tool for signal processing and finds numerous applications in various fields such as audio compression, pattern recognition, texture discrimination, computer graphics etc.

Specifically the 2-D DWT and its counterpart 2- D Inverse DWT (IDWT) play a significant role in many image/video coding applications. The DWT architecture, the input image is decomposed into high pass and low pass components using HPF and LPF filters giving rise to the first level of hierarchy. The process is continued until multiple hierarchies are obtained. A1 and D1 are the approximation and detail filters

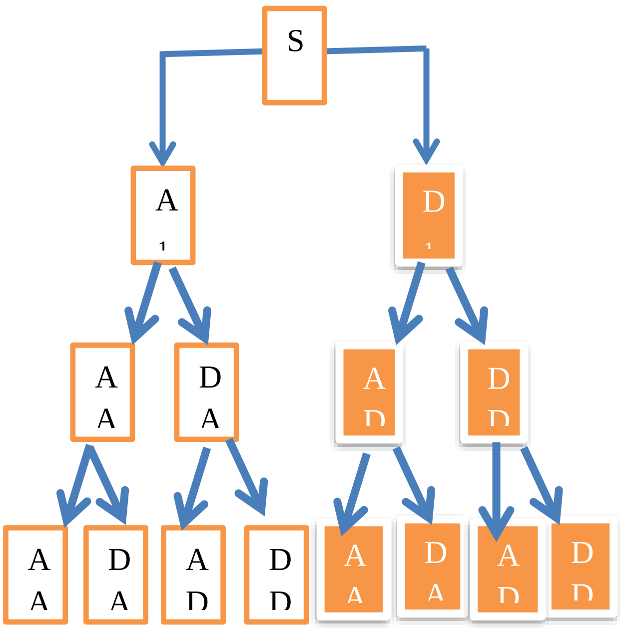


Figure 3.3: DWT Decomposition

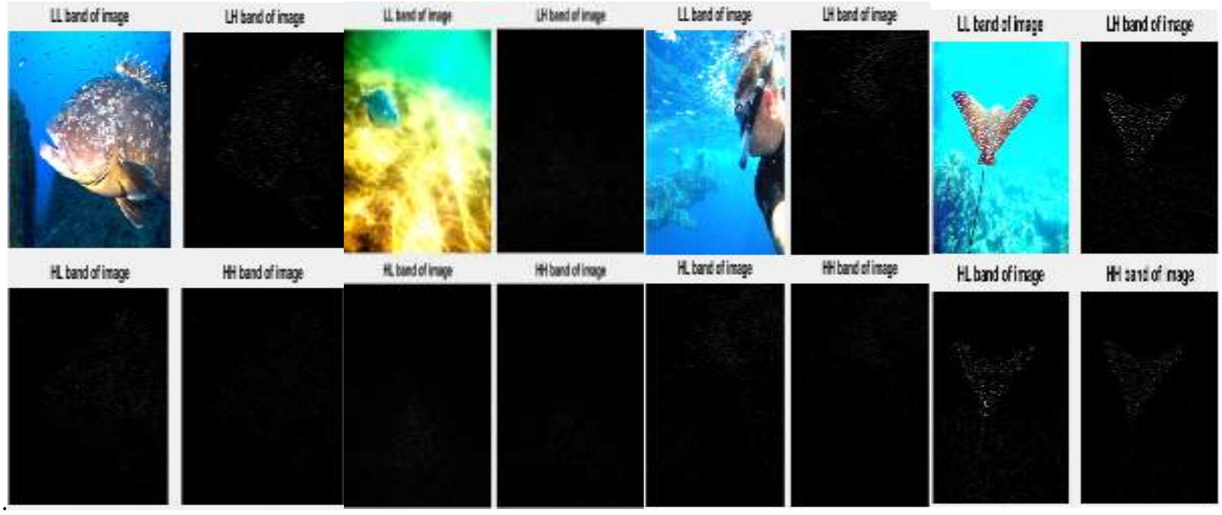


Figure: 3.4: DWT Output image

3.4.3-WAVELENGTH COMPENSATION AND IMAGE DEHAZING

The actual environment of underwater photography is as seen in Figure 1. Natural light from above the water attenuates while traveling to underwater depth D to illuminate the underwater scene. At x, a point within the scene, the reflected light travels a distance of $d(x)$, to the camera to form the image. Color scatter is a result of light absorption and multiple scattering by suspended particles on the way to the camera; color cast is due to the inconsistent attenuation of light at different wavelengths and occurs in both the depth D and the distance $d(x)$, Within the depth range R from the top of the image (D) to the bottom (D+R), the degree of attenuation varies in each area of the image, thereby necessitating estimation of underwater depth at each point for compensation. In general, to overcome insufficient lighting in an underwater photographic environment, an artificial light source such as L is used to assist photography. While compensating the energy lost in attenuation within the depth range, the luminance contributed by L must be considered to avoid overcompensation. The WCID algorithm follows an underwater image model for reverse compensation by first removing color scatter and color cast from distance $d(x)$, and then restoring the color cast from depth D. The amount of energy attenuated within the image range R and the luminance of the artificial light source L are then considered before carrying out appropriate compensation. The following section discusses the estimation of $d(x)$, depth D, artificial light source L, and depth range R as well as the procedure for energy compensation.

The underwater image of light after scattering can be expressed as the weighted sum of directly transmitted reflected light and scattered background light.

$$I_\lambda(x) = J_\lambda(x)t_\lambda(x) + B_\lambda(1 - t_\lambda(x)), \lambda \in \{R, G, B\}, \qquad (1)$$

$$t_\lambda(x) = \frac{Eo(\lambda, d(x))}{E_I(\lambda, 0)} = 10^{-\beta(\lambda)d(x)} = (\mathrm{Re}\, r(\lambda))^{d(x)}, \qquad (2)$$

Where x is a point in the image; λ is the wavelength of the light; $I_\lambda(x)$ is the image captured by the camera; $I_\lambda(x)$ is the reflected light that is directly transmitted. Light attenuates when passing through a medium [5]; the residual energy ratio $\mathrm{Re}\, r$ indicates the ratio of residual energy to initial energy for every unit of distance. Supposing the energy of a light beam before and after it passes through a medium with a length of d(x) is $E_I(\lambda, 0)$ and $Eo(\lambda, d(x))$ respectively; $t_\lambda(x)$ represents the residual energy ratio of the light beam after passing through the medium. Due to the fact that $t_\lambda(x)$ depends on wavelength λ and d(x), the distance between x and the camera, $t_\lambda(x)$, causes color scatter and color cast. The $\mathrm{Re}\, r$ of various light wavelengths differ in water [6]. As illustrated in Figure 1b, red light possesses longer wavelength and lower frequency, thereby attenuating faster than blue light. This results in the blueness of most underwater images.

In addition to wavelength, the residual energy ratio $t_\lambda(x)$ is also influenced by the salt ratio in the water. Using the amount of suspended particles and salt ratio, ocean water falls into three categories: general ocean water (Ocean Type 1), turbid tropical-subtropical water (Ocean Type 2), and mid-latitude water (Ocean Type 3). For every meter of general ocean water that a light beam passes through, the $\mathrm{Re}\, r$ values of red light (700μm), green light (520μm), and blue light (440μm) are 82 %, 95 %, and 97.5 %. The Rer in various environments can be adjusted with general ocean water as the standard.

Suppose an incident light beam A from the air forms background light B at depth D after attenuation and multiple scattering; background light is in correspondence with the brightest portion of the image. The relationship between incident light beam A and background light B can be expressed with an energy attenuation model:

$$E_B(\lambda, D) = E_A(\lambda, 0) \times (\mathrm{Re}\, r(\lambda))^D, \lambda \in \{R, G, B\} \quad (3)$$

Where $E_A(\lambda, 0)$ and $E_B(\lambda, D)$) are the energy of the incident light and the background light with wavelength λ. The $\mathrm{Re}\, r$ values of various wavelengths are:

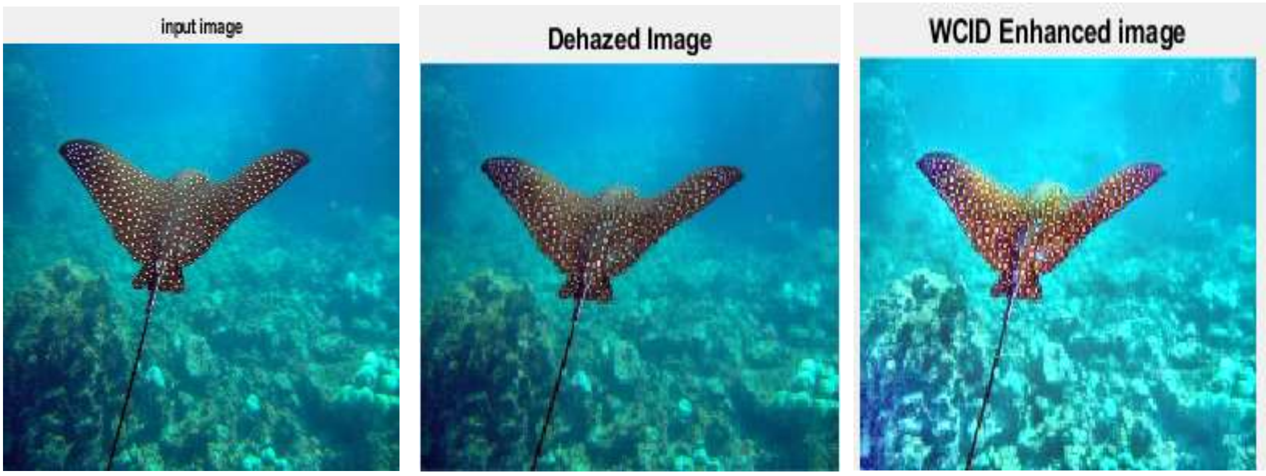
$$(\mathrm{Re}\, r(\lambda)) = \begin{cases} 0.8 \sim 0.85 \;\; if\, \lambda = 650 \sim 750 \mu m \\ 0.93 \sim 0.97 \, if\, \lambda = 490 \sim 550 \mu m \\ 0.95 \sim 0.99 \, if\, \lambda = 400 \sim 490 \mu m \end{cases} \quad (4)$$

Conventionally, the processing of underwater images is directed either towards calibrating distortion from color scatter or from color cast. Research on improving the former has included applying the properties of polarizers to enhance image contras and visibility, using image dehazing to eliminate hazing effects and enhance image contrast, and combining point spread functions (PSF) and modulation transfer function (MTF) in coordination with wavelet decomposition to enhance the high frequency areas in images and increase visibility. Although the approaches above can augment contrast and sharpen images, they cannot solve the issue of color cast. Research regarding improvement of color cast includes using the properties of light transmitting through water to provide energy compensation using the attenuation differences between various wavelengths and employing histogram equalization on underwater images to balance the luminance distributions of color. Despite the improvement in the color distortion of objects, these methods cannot repair the image blurriness caused by color scatter. The WCID algorithm proposed in this study combines a dehazing algorithm and energy compensation. Dark channel prior is used to estimate the distance of the object to the camera, and the dehazing algorithm removes the hazing effects caused by color scatter. Once underwater background light and the $\mathrm{Re}\, r$ values of various wavelengths of light are used to estimate the depth of the underwater scene, reverse compensation according to each wavelength is carried out to restore the color cast from water depth. With WCID, expensive optical instruments or distance estimation by two images is no longer required; WCID can effectively enhance visibility in underwater images and restore the original colors, obtaining high quality visual effects.

(i) (ii) (iii)

(i) **(ii)** **(iii)**

(i) **(ii)** **(iii)**



(i) **(ii)** **(iii)**

Figure 3.5: WCID algorithm output

3.5-INVERSE DISCRETE WAVELET TRANSFORM

In IDWT LL band of image, enhanced using WCID algorithm combined with other higher bands of image using IDWT.

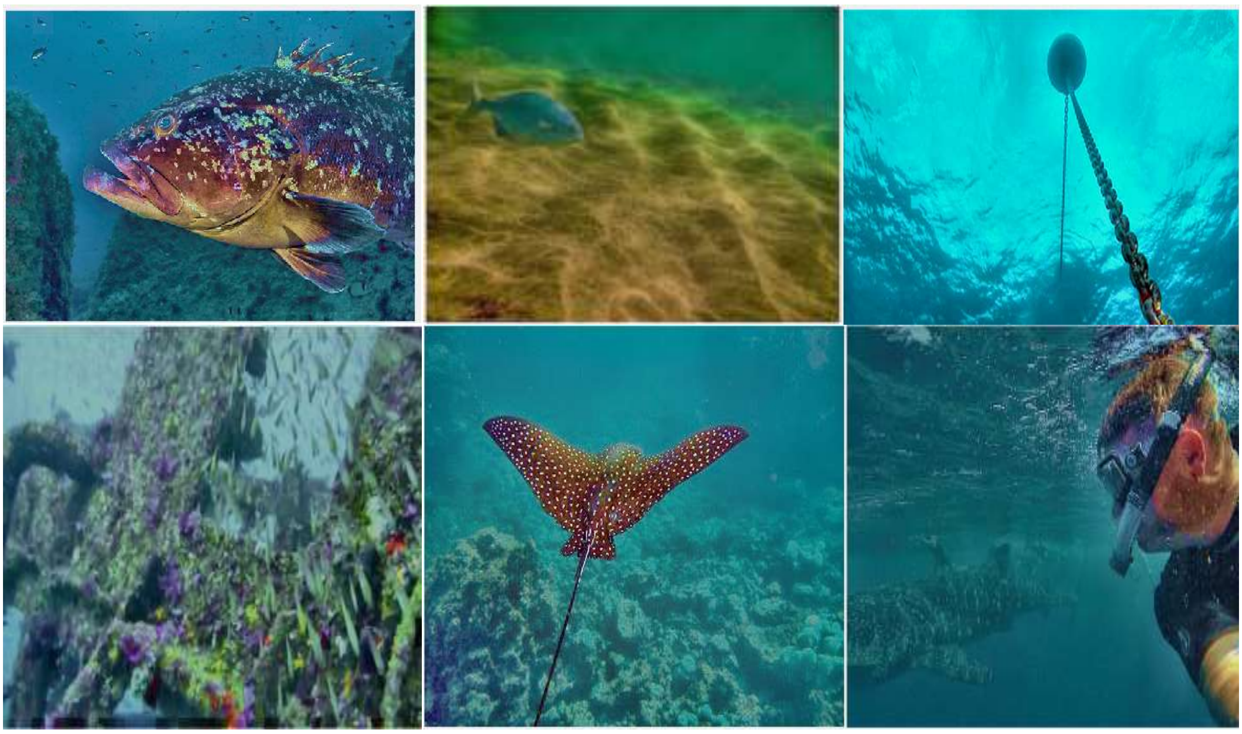


Figure 3.6: Images after IDWT

4-RESULTS AND DISCUSSION:

4.1 SIMUATION RESULTS

In this article, our proposed work has shown better throughputs in terms of PSNR and MSE.

4.2-PSNR: Peak signal-to-noise ratio, often abbreviated PSNR, is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots(10)$$

4.3-MSE: The measure of mean squared error requires a target of prediction or estimation along with a predictor or estimator which is said to be the function of the given data. MSE is defined as the average of squares of the "errors".

$$MSE(\bar{X}) = E[(\bar{X}-\mu)^2] = \left(\frac{\sigma}{\sqrt{n}}\right)^2 = \frac{\sigma^2}{n} \quad \ldots\ldots \quad (11)$$

Where,

σ is the population variance.

Table 4.1: Results of proposed technique in terms of PSNR and MSE

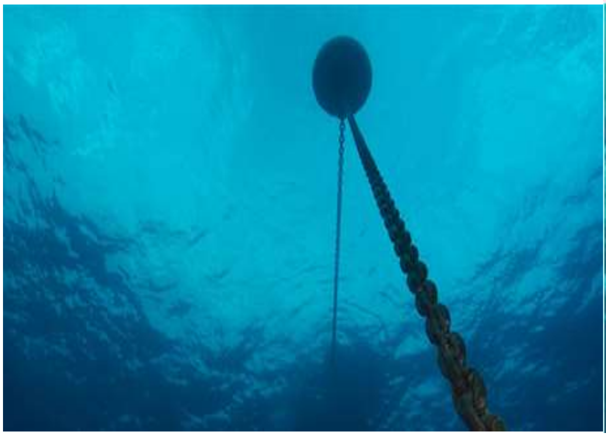
Input	**PSNR**	MSE
Image 1	58.6796	0.0234
Image 2	55.3418	0.0122
Image 3	57.1349	0.0187
Image 4	54.9839	0.0212
Image 5	56.6609	0.0129
Image 6	56.3726	0.0097

Input Image 1

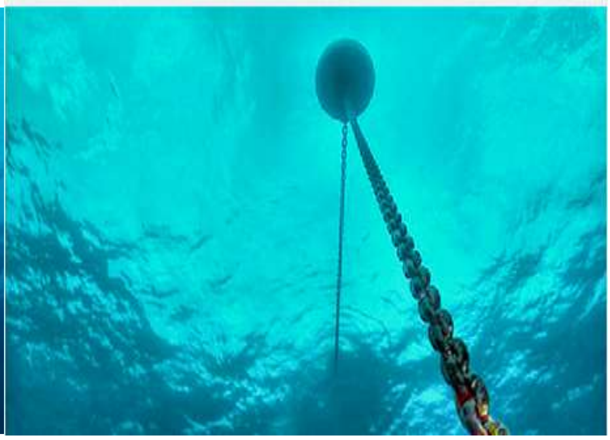
Output Image 1

Input Image 2

Output Image 2



Input image 3



Output Image 3

Input Image 4

Output Image 4

Input Image 5

Output Image 5

Input Image 6

Output image 6

Figure 4.1: Shows input and output images

In above figure all the inputs hazed images are depicted with enhanced and dehazed image. It can noticed that output dehazed images are better and light particles has been removed to better level. We have depicted values in terms of PSNR and MSE, those value shows quality of dehazed images w.r.t input dataset.

4.4-FUTURE SCOPE AND CONCLUSION

In the proposed work we have achieved results up to expected level, which can be noticed from the figure and table. In these citations we have depicted images quality and in term of values too.

In this article, we have enhanced image quality by enhancing in time as well as in the frequency domain. Particle's available in the water, which are responsible for haze has been removed using WCID algorithm. Suspended particles mainly constitute sand and light penetrated into water.

This research can be taken to the next step, by working on the object detection which has been enhanced in the article.

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