UNDERWATER IMAGE ENHANCEMENT THROUGH DEHAZING AND COLOR CORRECTION TECHNIQUES

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***Abstract-** Underwater photography and videography suffer from significant challenges due to the inherent properties of water, such as light absorption, scattering, and colour distortion. When capturing images or videos underwater, the medium's particulate matter and water molecules cause haze and loss of colour fidelity, resulting in poor visual quality and reduced visibility. To address these issues and improve the overall quality of underwater imagery, researchers have developed various image enhancement techniques that aim to dehaze the images and correct colour distortions. The traditional approach to underwater image enhancement involved simple post-processing methods, such as contrast stretching and histogram equalization. While these techniques might help to some extent, they often fail to produce satisfactory results due to the complex and non-linear nature of underwater light attenuation and scattering. Moreover, these methods are not specifically designed for addressing the unique challenges posed by underwater environments, leading to limited improvements in image quality. Therefore, the need for effective underwater image enhancement techniques arises from several factors such as, underwater imagery is crucial in various fields, including marine biology, underwater exploration, environmental monitoring, and underwater archaeology. In addition, high-quality images are essential for accurate data analysis and interpretation. Further, an improved underwater image quality aids in enhancing the capabilities of underwater robotics, surveillance systems, and underwater imaging devices. Thus, this project presents an innovative and comprehensive approach to address the challenges associated with underwater imagery. The study proposes a novel combination of dehazing, and colour correction techniques tailored specifically for the unique characteristics of underwater environments.*

***KEYWORDS:** Color fidelity, Underwater Imagery, Underwater Exploration, Environmental Monitoring, Data analysis.*

I. INTRODUCTION

Underwater images get degraded due to poor lighting conditions and natural effects like bending of light, denser medium, reflection of light and scattering of light etc. As the density of sea water is 800 times denser than air, when light enters from air (here lighting source) to water, it partly enters the water and partly reflected reverse. More than this, as light goes deeper in the sea, the amount of light enters the water also starts reducing. Due to absorption of light in the water molecules, underwater images will be darker and darker as the deepness increases. Depending on the wavelength also, there will be colour reduction. Red colour attenuates first followed by orange. As the blue colour is having shortest wavelength it travels longest in seawater there by dominating blue colour to the underwater images affecting the original colour of the image.

The overall performance of underwater vision system is influenced by the basic physics of propagation of light in the sea. The overall performance of underwater vision system is influenced by the basic physics of propagation of light in the sea. One must take care about absorption and scattering of light when considering underwater optical imaging systems. Most often accurate values of attenuation and thorough knowledge of forward and backward scatter is required for restoring underwater images performance of underwater vision system is influenced by the basic physics of propagation of light in the sea. One must take care about absorption and scattering of light when considering underwater optical imaging systems. Most often accurate values of attenuation and thorough knowledge of forward and backward scatter is required for restoring underwater images.

Due to apprehension regarding the present conditions of the world's oceans many large-scale scientific projects have instigated to examine this. The underwater video sequences are used to monitor marine species. Underwater image is inundated by reduced visibility conditions making images deprived of colour variation and contrast. Due to this restriction other methods like sonar ranging have been preferred previously. Since alternate methods yield poor resolution images which are hard to understand, nowadays for close range studies visible imaging are preferred by scientists. The emphasis of these work deceits primarily in the area of implementation of vision system which involves analysis of enhanced images.

Image enhancement techniques are usually divided in frequency domain and spatial domain methods. The frequency domain methods are normally based on operations in the frequency transformed image while spatial domain methods are based on direct manipulation of the pixels in the image itself.

II. RELATED WORK

In article it is potential to eliminate the complex interference and rebuild the underwater images by enhancement techniques. The underwater images are enhanced by using the algorithms like grey world for clearance and dark channel prior for processing of underwater images by applying the BP network for restoration of details in the underwater image. The TV model procedure is executed because to covering the blank area after the recognition and elimination of object. The article describes the enhancement technique by using the wavelet fusion for underwater images which is due to the absorption and reflection of light while capturing the images in water. By using this implementation, we can evaluate and Dehazed or enhance the contrast and color of the image.

Owing to the scattering and absorption of light color alteration is emerged in underwater images. For improving the underwater images color distortion CC-Net is used and for contrast enhancement we are using HR-Net which consist of single transmission coefficient. These two Nets are the grouping of UIE-Net which is one of the frameworks in CNN architecture. This implementation progresses the learning process and convergence speed simultaneously. It overcomes the several optical transmissions, hazing and color distortions. For features extraction these two are trained to the CNN framework.

G. Yadav, S. Maheshwari and A. Agarwal research in describe that in order to raise the visibility of the hazy image or video we utilize the contrast limited adaptive histogram equalization. When compared to other enhancement techniques MEF algorithm gives better enhancement results because it applies for both color and grey images for both regions. A new frame is generated after the adjustment of intensity values over the image is named as histogram equalization.

Based on the neighbouring pixel values AHE adjust the intensity levels over a particular region of any fog (homogeneous) type of images only. For histogram equalization shape in MEF Distribution parameter is utilized. For noisy image we are applying clip limit.

The light travelling in the water with altered wavelengths leads to the color variation due to the attenuation. Here, by employing the image processing techniques we can enhance the underwater images. In this paper we have both enhancement and restoration operations. There are different types of image enhancement techniques for enhancing the image.

Image restoration is nothing, but the degradation is used to restore the loss of information. In this paper, UIQM is utilized for measuring the quality of the underwater images. This implementation gives the better-quality results when compared with other enhancement techniques.

These research papers highlight the continuous efforts to develop innovative techniques and tools for enhancing underwater images, catering to a wide range of applications in marine science, environmental monitoring, underwater archaeology, and more. As technology advances, the field of underwater image enhancement continues to evolve, contributing to a deeper understanding and appreciation of underwater images.

In authors proposed the deep learning architecture for underwater image enhancement using the white-balancing-Multiple Underexposure versions reduction prior (WB-MUV) model. The WB-MUV method for enhancing the underwater images is by using the deep residual architecture. This is one of the networks in CNN which is used to convert the low-resolution image into high resolution image. The underwater images are less in contrast and color distortion. Generally, we are considering the input image as reference.

First, we consider a cell after training the dataset. Here we are using the YCbCr color space for conversion of input image and the whole procedure is performed in Y component only. By utilizing the bicubic interpolation we can change the image into low resolution image. For bicubic interpolation, the block uses the weighted average of four transformed pixel values for each output pixel value.

To overcome the drawbacks of the WB-MUV approach, we are using different layers of DLCNN for enhancing the underwater images including such as BN layer, ResNet layer and CycleGAN. The resultant enhanced underwater image has less visibility and contrast. Edge difference loss (EDL) plays a significant role in order to know the pixel difference between the two images.

Mostly in case of WB-MUV usage of MSE loss in more to calculate the peak signal to noise ratio (PSNR). The depth which we are using in this process is 20.

The low-resolution image is resized based on the reference image size and difference is measured between them. The combination of the resultant upscale and difference images is called as the train data. The residual network is trained after assigning the layers and training options. In order to get the high-resolution image, the difference image is calculated by considering the test image. For WB-MUV technique of enhancement there is no need of same size of images are needed. By training the proper dataset it gives the better results of enhanced image.

III. PROPOSED WORK

This research provides underwater image enhancement using a technique called "ULAP" (Underwater Light Absorption Prior). The project’s main goal is to improve the visual quality of underwater images by compensating for the effects of light absorption and scattering that occur when capturing images underwater. Here's an overview of the project:

Step – 1: Input Images: The project starts by processing a set of input images located in a folder called "Input Images."

Step – 2: Depth Map Estimation (depthMap function)

- The first step is to estimate a depth map for each input image. The depth map represents the perceived depth or distance of objects in the underwater scene.
- The depth map is computed based on predefined coefficients (theta_0, theta_1, theta_2).

Step – 3: Global Histogram Stretching (global_stretching function): After estimating the depth map, a global histogram stretching operation is applied to enhance the contrast and details in the depth map.

Step – 4: Atmospheric Light Estimation (BLEstimation function)

- The atmospheric light, often referred to as the "AtomsphericLight," is estimated based on the input image and the depth map.
- The atmospheric light represents the intensity of the ambient light in the scene and is crucial for correcting the image.

Step – 5: Minimum Depth Calculation (minDepth function): The minimum depth value for the image is calculated using the estimated atmospheric light. This depth value is used in subsequent computations.

Step – 6: Transmission Map Estimation (getRGBTransmissionESt function)

- RGB transmission values are estimated based on the depth map and the minimum depth value.
- The transmission map describes how much light is transmitted through the water at different points in the image.

Step – 7: Transmission Map Refinement (refinedtransmissionMap function): The transmission map is refined using a guided filter. Guided filtering helps improve the quality of the transmission map.

Step – 8: Scene Radiance Calculation (sceneRadianceRGB function):

- The final step involves calculating the scene radiance of the enhanced image.
- Scene radiance represents the true color and intensity of objects in the underwater scene.

Step – 9: Output Images

- The enhanced image, transmission map, and depth map are saved in an "Output Images" folder.
- The enhanced image is the final result of the underwater image enhancement process.

Step – 10: Display and Evaluation

- The code displays both the input and enhanced images using OpenCV.
- It calculates and prints quality metrics, including PSNR (Peak Signal-to-Noise Ratio), MSE (Mean Squared Error), and SSIM (Structural Similarity Index), to evaluate the quality of the enhanced image.

Step – 11: Timing: The code records the time taken for the entire image processing pipeline and prints the elapsed time.

Step – 12: Loop Through Input Images: The code processes multiple input images one by one, repeating the above steps for each image.

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.
The Unified Modelling Language Is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS: The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modeling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

3.1 Class Diagram

The class diagram is used to refine the use case diagram and define a detailed design of the system. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an “is-a” or “has-a” relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed “methods” of the class. Apart from this, each class may have certain "attributes" that uniquely identify the class.

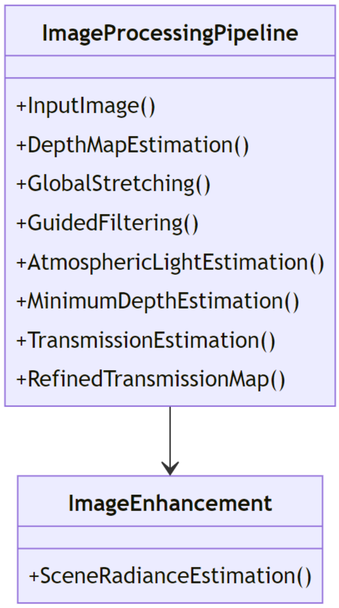

Fig 3.1: class diagram

3.2 Data flow diagram

A Data Flow Diagram (DFD) is a visual representation of the flow of data within a system or process. It is a structured technique that focuses on how data moves through different processes and data stores within an organization or a system. DFDs are commonly used in system analysis and design to understand, document, and communicate data flow and processing.

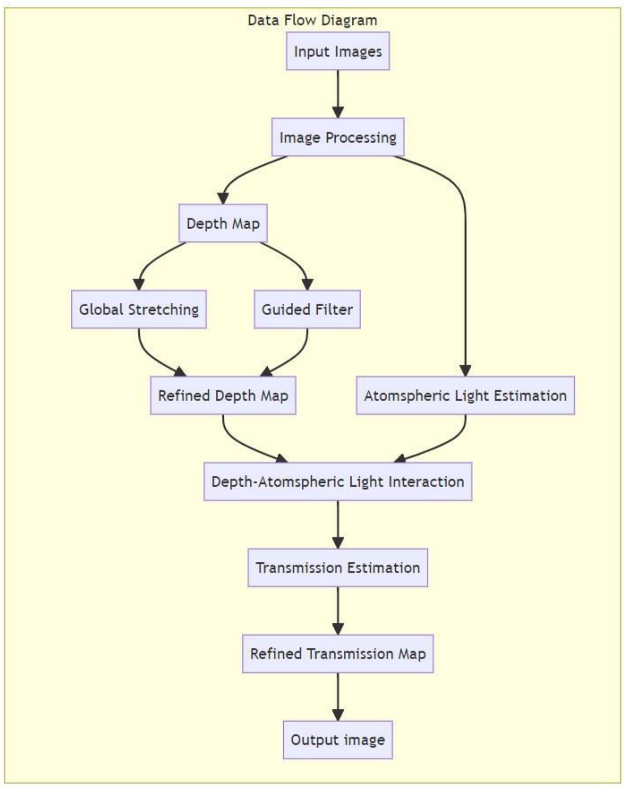

Fig 3.2: Data Flow Diagram

3.3 Sequence Diagram

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows, as parallel vertical lines ("lifelines"), different processes or objects that live simultaneously, and as horizontal arrows, the messages exchanged between them, in the order in which they occur. This allows the specification of simple runtime scenarios in a graphical manner.

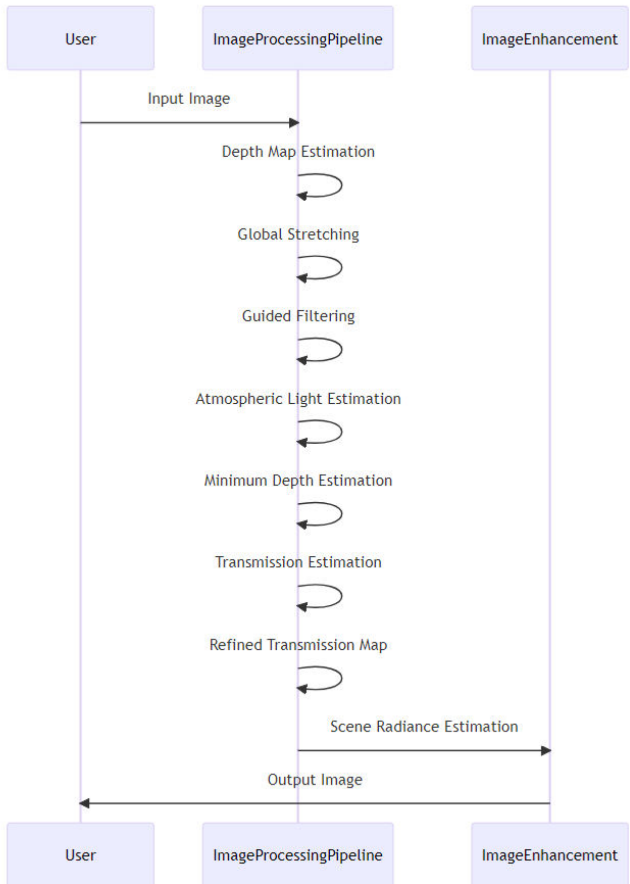

Fig 3.3: Sequence Diagram

3.4 Activity diagram

Activity diagram is another important diagram in UML to describe the dynamic aspects of the system.

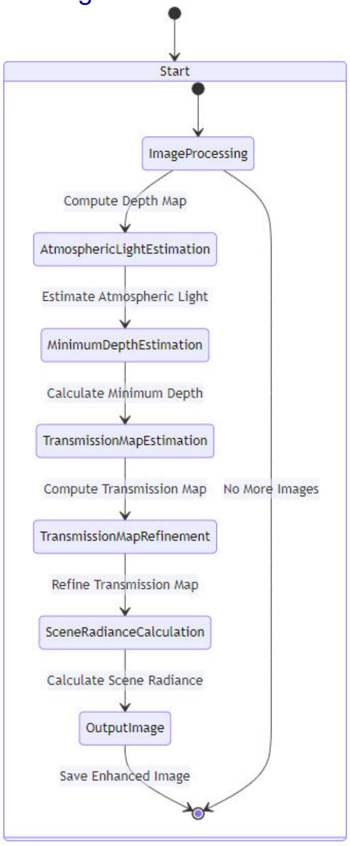

Fig 3.4: Activity Diagram

IV. EXPERIMENTAL ANALYSIS

4.1 Implementation description

This project is mainly designed to enhance the visibility and quality of underwater images by estimating the atmospheric light, calculating depth maps, and applying various image processing techniques to improve image clarity. It also provides options for performance evaluation using standard image quality metrics. Here's a detailed description of the code:

Importing Libraries:

os: For interacting with the file system.

datetime: For measuring execution time.

numpy (as np): For numerical operations on arrays.

cv2 (OpenCV): For computer vision and image processing.

natsort: For natural sorting of file names.

skimage.metrics.structural_similarity: For calculating structural similarity (SSIM) between images.

GuidedFilter: It seems that there is a reference to a GuidedFilter class, but the actual implementation of this class is not shown in the provided code.

BLEstimation Function:

This function estimates the atmospheric light of an input image based on the provided depth map.It takes an input image (img) and a depth map (DepthMap) as inputs.The code calculates the atmospheric light and returns it as A_1.

depthMap Function:

This function computes the depth map of an input image using a set of predefined coefficients. It takes an input image (img) as input. The depth map is calculated based on the image's color channels, and the result is returned as DepthMap.

minDepth Function:

This function calculates the minimum depth of an underwater scene based on the input image and the estimated atmospheric light. It takes the input image (img) and the atmospheric light (BL) as inputs. The code computes the minimum depth and returns it as min_depth.

getRGBTransmissionESt Function:

This function calculates the RGB transmission values based on a given depth map.It takes the depth map (depth_map) as input and computes transmission values for the three color channels (B, G, R).The transmission values are returned as transmissionB, transmissionG, and transmissionR.

global_stretching Function:

This function performs global histogram stretching on an input image.It takes the input image (img_L) and applies histogram stretching to enhance image contrast.

GuidedFilter Class:

This is an implementation of a guided filter class, but the details of the class and its methods are not fully provided in the code snippet.

refinedtransmissionMap Function:

This function refines the transmission map using a guided filter. It takes the initial transmission values for the three-color channels (transmissionB, transmissionG, transmissionR) and the input image (img) as inputs. The refined transmission map is returned as transmission.

sceneRadianceRGB Function:

This function calculates the scene radiance of an underwater image based on the transmission map and atmospheric light. It takes the input image (img), transmission map (transmission), and atmospheric light (AtomsphericLight) as inputs. The enhanced scene radiance image is returned.

Main Loop:

The main loop iterates through a folder containing input images of underwater scenes.

For each image, it performs the following steps:

Calculates the depth map and refines it.

Estimates the atmospheric light.

Computes the transmission values.

Refines the transmission map.

Calculates the enhanced scene radiance.

Saves the enhanced image and transmission map as output.

Performance Metrics: The code defines functions to calculate performance metrics such as PSNR (Peak Signal-to-Noise Ratio), MSE (Mean Squared Error), and SSIM (Structural Similarity Index) between the original and enhanced images. These metrics are not calculated within the code but are available for potential use.

Execution Time Measurement: The code measures the execution time of the entire processing pipeline and prints it.

Display and Saving: The code displays the input and output images for each input image and waits for user interaction. The enhanced images and transmission maps are saved in the "OutputImages" directory.

4.2 Results description

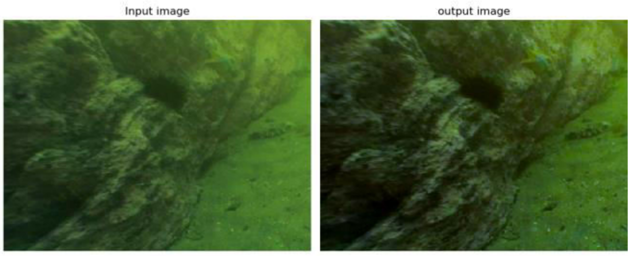

Fig 4.2.1: Underwater performance enhancement on sample image 1.

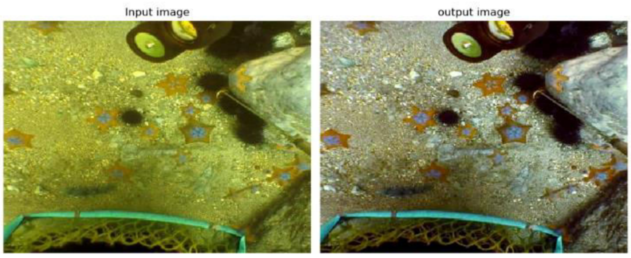

Fig 4.2.2: Underwater performance enhancement on sample image 2.

Fig 4.2.3: Underwater performance enhancement on sample image 3.

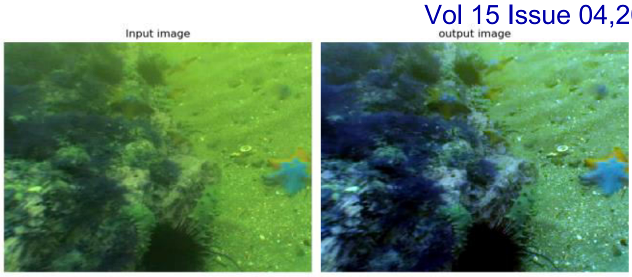

Fig 4.2.4: Underwater performance enhancement on sample image 4.

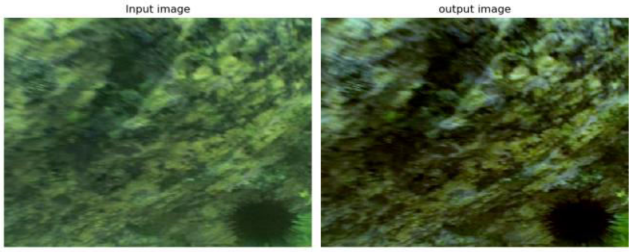

Fig 4.2.5: Underwater performance enhancement on sample image 5.

Table 1 offers a comprehensive performance comparison of various metrics for a set of five distinct image samples. These samples represent different underwater images that have undergone enhancement using proposed model. The table assesses the quality and effectiveness of the enhancement techniques employed by quantifying three essential metrics: Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM).

The "PSNR (in dB)" column in the table reports the PSNR scores in decibels (dB) for each of the five image samples. PSNR is a widely used image quality metric that measures the ratio of the maximum possible power of a signal to the power of noise that distorts it. Higher PSNR values are indicative of superior image quality. Among the samples, Sample 3 exhibits the highest PSNR value at 48.93 dB, suggesting exceptional image quality, while Sample 5 has a PSNR of 47.72 dB, indicating slightly lower quality.

The "MSE" column presents the Mean Squared Error values for the same image samples. MSE quantifies the average squared difference between the original and processed images. Smaller MSE values are preferable, as they signify better image quality. The "SSIM" column in the table provides the Structural Similarity Index scores for each sample. SSIM assesses the structural similarity between two images, considering factors such as luminance and contrast. SSIM values range from -1 to 1, with 1 indicating perfect similarity. Higher SSIM values correspond to improved image quality. Among the samples, Sample 3 stands out with the highest SSIM score of 0.8585, signifying strong structural similarity. Conversely, Sample 5 exhibits a lower SSIM of 0.7315, suggesting less similarity with the original image.

Lastly, the "Average" row calculates the mean values of the metrics across all the samples. These average values provide a holistic assessment of the overall performance of the image enhancement or processing technique applied to the samples. In this case, the average PSNR is 48.126 dB, the average MSE is 1.006, and the average SSIM is 0.80826. These averages offer valuable insights into the overall quality of the image enhancement process, with higher PSNR and SSIM and lower MSE indicating more effective enhancement techniques.

V.CONCLUSION

This paper utilized the ULAP technique for underwater image enhancement, demonstrates a significant improvement over traditional methods like histogram equalization. This project leverages a physics-based approach, taking into account the intricate interactions between light and water in underwater environments. As a result, it offers a range of advantages, including depth-aware enhancement, atmospheric light estimation, transmission map modeling, and guided filtering for noise reduction. Furthermore, the incorporation of quality metrics facilitates an objective evaluation of the enhancement process. One of the standout features of ULAP is its adaptability to varying underwater conditions. It achieves this through the estimation of depth maps, allowing for context-aware enhancements that consider the depth-related variations in the scene. This depth awareness is particularly valuable in underwater imaging, where objects are often located at different depths, each requiring tailored correction. Atmospheric light estimation, another key element of ULAP, enhances the correction process by accurately compensating for light absorption and scattering. This ensures that the final enhanced images better represent the true colors and features of the underwater scene, a critical factor in underwater research, exploration, and surveillance.

5.1 Future Scope

The ULAP-based underwater image enhancement project offers several avenues for future research and development such as developing user-friendly graphical interfaces can make ULAP accessible to a wider range of users, including marine scientists, photographers, and underwater explorers. Extending the project to include object detection and recognition capabilities can be invaluable for underwater surveillance, wildlife monitoring, and archaeological exploration.

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