PROJECT REPORT ON

EFFICIENT UNDERWATER IMAGE RESTORATION USING DOUBLE-OPPONENCY LIGHT ESTIMATION AND GREEN CHANNEL PRIOR

Submitted in partial fulfilment of the Requirement for the award of the degree of

BACHELOR OF TECHNOLOGY
IN
ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

Project Associates	Regd. Nos
Gowni Keerthi	20091A0470
Kamsali Jaswanth Singh	20091A0455
Mekhala Sreekanth	20091A04J5
Shaik Shashavali	20091A04H2

Under the Esteemed Guidance of
Smt. M. MAHESWARI
M.Tech. (Ph.D)
Assistant Professor

(ESTD-1995)

DEPARTMENT OF
ELECTRONICS AND COMMUNICATION ENGINEERING

RAJEEV GANDHI MEMORIAL COLLEGE OF ENGINEERING AND TECHNOLOGY
(AUTONOMOUS)
Affiliated to JNTUA - Anantapuramu, Approved by AICTE - New Delhi,
Accredited by NBA - New Delhi, Accredited by NAAC with A+ Grade – New Delhi
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RAJEEV GANDHI MEMORIAL COLLEGE OF ENGINEERING & TECHNOLOGY

AUTONOMOUS

(Approved by A.I.C.T.E - New Delhi, Affiliated to JNTUA - Anantapuramu, Accredited by NBA - New Delhi, Accredited by NAAC with 'A+' Grade - New Delhi)

NANDYAL – 518 501, A.P, India

CERTIFICATE

This is to certify that the dissertation entitled "EFFICIENT UNDERWATER IMAGE RESTORATION USING DOUBLE-OPPONENCY LIGHT ESTIMATION AND GREEN CHANNEL PRIOR" is being submitted by Gowni Keerthi (20091A0470), Kamsali Jaswanth Singh (20091A0455), Mekhala Sreekanth (20091A04J5), Shaik Shashavali (20091A04H2) under the guidance of Smt. M. Maheswari, Assistant Professor for Project of the award of B.Tech Degree in Electronics and Communication Engineering, Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal (Autonomous) (Affiliated to JNTUA Anantapuramu) is a record of bonafide work carried out by them under our guidance and supervision.

Dr. Kethepalli Mallikarjuna
Head of the Department

Smt. M. Maheswari
Project Guide

Signature of the External Examiner

Date of Viva-Voce:

CANDIDATE'S DECLARATION

We hereby declare that the work done in this project titled "**Efficient Underwater image restoration using Double Opponency light Estimation and Green Channel Prior**" submitted towards completion of main project in IV Year II Semester of B. Tech (ECE) at the **Rajeev Gandhi Memorial College of Engineering & Technology (Autonomous),** Nandyal. It is an authentic record our original work done under the guidance of **Dr. D. Satyanarayana, Professor,** Dept. of ECE, RGMCET, Nandyal. We have not submitted the matter embodied in this major Project for the award of any other degree in any other institution.

Project Associates	**Regd. Nos**	**Signatures**
Gowni Keerthi	20091A0470	
Kamsali Jaswanth Singh	20091A0455	
Mekhala Sreekanth	20091A04J5	
Shaik Shashavali	20091A04H2	

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Project Associates	**Regd. Nos**
Gowni Keerthi	20091A0470
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Shaik Shashavali	20091A04H2

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ABSTRACT

Underwater images are crucial for marine exploration and various applications, suffer from color bias and low contrast due to light absorption and scattering. Traditional restoration methods like deblurring methods, multi-model fusion and other techniques which are time- consuming and yield unsatisfactory results. In this project, presented an innovative underwater image restoration technique. Leveraging the concept of human visual color constancy, Double-opponency and the green channel prior are employed accurately estimate underwater light values and compensate for color distortion.

This method first deals with the original underwater image using two independent processes. One process estimates the value of background light and transmission to solve major degradation problems and the other process performs contrast stretching. The output of two processes is subsequently fused in the hue, saturation, value (HSV) color space to obtain final output image.

This approach significantly enhance color accuracy and contrast in the restored images and provides remarkable efficiency, reducing computation time substantially compared to existing methods, while ensuring high-quality image restoration. This technique hold great promise for real-world underwater applications.

CHAPTER – I

INTRODUCTION

1.1 Introduction

In recent years, underwater imaging has emerged as a crucial tool for various scientific, industrial, and recreational purposes. From marine biology and environmental monitoring to underwater archaeology and oil exploration. The need for high-quality underwater imagery has become increasingly pronounced. However, capturing clear and detailed images underwater presents unique challenges due to factors such as light attenuation, water turbidity, and backscatter. Underwater environments inherently distort and attenuate light, leading to decreased visibility and image quality. These challenges are compounded by the scattering of light off suspended particles and organisms in the water column, further obscuring details and reducing contrast. As a result, underwater images often suffer from poor sharpness, color fidelity, and contrast, making interpretation and analysis difficult.

To address these challenges, researchers and engineers have developed various techniques and technologies for underwater image clarification. These methods aim to enhance image quality by mitigating the effects of light attenuation, turbidity, and scattering, thereby improving visibility and increasing the usability of underwater imagery. In this project, we provide an overview of the key challenges associated with underwater imaging and review the current state-of-the-art techniques for underwater image clarification. We discuss both traditional approaches, such as image restoration and enhancement algorithms. Additionally, we highlight the applications and implications of underwater image clarification across different domains, from marine research and conservation to underwater robotics and autonomous systems.

The exploration of marine resources is crucial for understanding and utilizing the vast wealth offered by Earth's oceans. Utilizing underwater vehicles to navigate these environments has become indispensable, with optical detection serving as the primary method for visual perception. Optical images, particularly in close-range operations, offer higher resolution and richer information compared to sonar images. However, despite their advantages, underwater images are often plagued by issues such as light scattering, absorption, and noise, leading to color bias, low contrast, and poor definition. Such degradation significantly impacts various applications like underwater archaeology, marine research, surveillance, and target tracking. Thus, improving underwater image quality through processing technology is essential for enhancing the performance of these applications.

1.2 Underwater image clarification

In recent years, underwater image clarification technology has made notable strides, offering impressive results and finding widespread application. Broadly, these methods fall into two categories: enhancement and restoration. Image enhancement adjusts pixel values to improve contrast and color without considering underwater imaging principles, while restoration relies on underwater imaging models to analyze degradation mechanisms and estimate parameters for image clarification. However, both approaches involve extensive calculations, resulting in long computation times to achieve clarity.

However, its reliance on sufficient and effective training data poses challenges, particularly in the underwater environment where obtaining corresponding ground truth data is difficult. Therefore, while effective in other domains, learning-based methods may not be suitable for underwater image clarification.

Our work aims to develop a less time-consuming underwater image clarification method that requires less training data, making it suitable for real underwater scenarios. This approach can significantly aid underwater equipment in swiftly detecting marine resources. In this project, we primarily focus on traditional restoration and enhancement methods.

With increasing demand for underwater detection equipment, underwater image clarification has garnered significant attention. Various methods have been proposed to tackle challenges like low contrast, color distortion, and uneven illumination. These include enhancement methods, restoration methods, and hybrid approaches combining both. Recent years have witnessed the introduction of learning-based methods, inspired by their success in other domains.

Overall, this project aims to provide insights into the field of underwater image clarification, offering a comprehensive understanding of the challenges, techniques, and applications involved. By addressing these challenges and advancing the state-of-the-art, we can unlock the full potential of underwater imaging for scientific, industrial, and recreational purposes, enabling new discoveries and innovations in the exploration and understanding of the underwater world.

From studying marine ecosystems and underwater archaeology to offshore engineering and military operations, the demand for clear and detailed underwater imagery has grown substantially.

1.3 Problems of Underwater images

Underwater environments inherently distort and attenuate light, leading to reduced visibility and degraded image quality. Light undergoes scattering and absorption as it travels through water, resulting in loss of contrast, color distortion, and diminished sharpness. Moreover, suspended particles and marine organisms contribute to backscatter, further obscuring details and complicating image interpretation.

1.4 Applications of Underwater image clarification

More recently, advancements in machine learning and computer vision have revolutionized underwater image clarification. Deep learning-based approaches, including convolutional neural networks (CNNs), have shown remarkable success in automatically learning to restore and enhance underwater images. These models can effectively handle complex image degradation and produce visually appealing results.

1.4.1 Underwater Robotics and Autonomous Systems

The clarity of underwater imagery directly impacts the performance of underwater robotics and autonomous systems. Autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) rely on onboard cameras to navigate and perform tasks such as underwater inspection, mapping, and search and rescue. Clearer images enable these systems to make more accurate decisions and operate more effectively in challenging underwater environments.

1.4.2 Marine Research and Conservation

In the realm of marine research and conservation, underwater imagery plays a vital role in studying and monitoring marine ecosystems. High-quality images are essential for identifying species, assessing habitat health, and tracking changes over time. By clarifying underwater images, researchers can gain deeper insights into underwater ecosystems and make more informed decisions for conservation efforts.

1.4.3 Underwater Archaeology and Cultural Heritage Preservation

Underwater archaeology relies heavily on imaging technologies to explore and document submerged archaeological sites. Clarifying underwater images is crucial for accurately identifying artifacts, documenting archaeological features, and preserving cultural heritage. Clearer images enhance the accuracy of archaeological surveys and facilitate the interpretation of underwater cultural landscapes.

1.4.4 Offshore Engineering and Infrastructure Inspection

In the field of offshore engineering and infrastructure inspection, underwater imaging is indispensable for assessing the condition of underwater structures such as oil rigs, pipelines, and bridges. Clear images enable engineers to detect defects, corrosion, and other anomalies, ensuring the integrity and safety of offshore installations. Effective image clarification techniques enhance the efficiency and accuracy of underwater inspections.

1.4.5 Aquaculture and Fisheries Management

Aquaculture operations and fisheries management benefit from underwater imaging for monitoring fish stocks, assessing aquaculture facilities, and studying fish behavior. Clearer underwater images enable farmers and researchers to track fish health, optimize feeding strategies, and manage aquaculture environments more effectively. Improved image quality enhances the productivity and sustainability of aquaculture operations.

1.4.6 Underwater Tourism and Recreation

Underwater tourism and recreational activities, such as scuba diving and snorkeling, rely on clear underwater visibility for an immersive and enjoyable experience. High-quality underwater images enhance the attractiveness of dive sites, allowing tourists to appreciate marine life and underwater landscapes. By clarifying underwater images, operators can promote tourism and ecotourism while raising awareness about marine conservation.

1.4.7 Security and Defence Applications

In security and defense applications, underwater imaging is essential for underwater surveillance, reconnaissance, and mine detection. Clear imagery enables security personnel and defense forces to monitor coastal borders, detect underwater threats, and conduct underwater search operations. Enhancing underwater image clarity enhances situational awareness and improves the effectiveness of maritime security operations.

CHAPTER – II

LITERATURE REVIEW

2.1 Unsupervised color equalization algorithm

Author : Chambah et al.

Chambah et al. (2004) introduced an unsupervised color equalization algorithm inspired by human visual adaptation mechanisms. The algorithm aimed to facilitate fish segmentation and feature extraction in underwater images by equalizing colors based on the human visual system's ability to adapt to different light and color conditions. By enhancing color consistency and reducing variations caused by underwater conditions, this approach automated the process of improving image quality, particularly beneficial for tasks requiring automated analysis like fish segmentation.

2.2 Characteristics of backscattered light

Author : Schechner and Karpel

Schechner and Karpel (2004) focused on exploiting the characteristics of backscattered light to enhance visibility in underwater images. By analyzing how light interacts with particles and surfaces underwater, the method aimed to mitigate the effects of backscatter, which often degrade image clarity and contrast. By processing backscattered light information, this approach sought to improve overall visibility in underwater scenes, aiding in the identification of objects and features.

2.3 Algorithm based on a simplified Jaffe-McGlamery model

Author : Trucco and Olmos-Antillon

Trucco and Olmos-Antillon (2006) developed an algorithm based on a simplified Jaffe-McGlamery model for underwater imaging. It aimed to restore degraded underwater images by addressing issues such as low contrast and color distortion. Operating under ideal assumptions of uniform illumination and forward-scattering, the algorithm provided a framework for automatic image restoration. However, real-world underwater conditions often deviate from these assumptions, posing challenges to its effectiveness.

2.4 Automatic pre-processing algorithm to address challenges

Author : Bazeille et al.

Bazeille et al. (2007) proposed an automatic preprocessing algorithm to address challenges like uneven lighting, noise, and artifacts in underwater images. By applying a combination of filters such as homomorphic, wavelet, and anisotropic filters, the algorithm corrected lighting inconsistencies, suppressed noise, and enhanced edges and textures. Through a series of preprocessing steps, it prepared underwater images for further analysis and enhancement, ultimately improving their quality and interpretability.

2.5 sliding stretch algorithm based on the hypothesis

Author : Iqbal et al.

Iqbal et al. (2007) introduced a sliding stretch algorithm based on the hypothesis of similar distributions for histograms of the red, green, and blue components of an ideal image. By stretching the value ranges of different color channels, the algorithm aimed to enhance overall image contrast and color fidelity. Adjusting the saturation and intensity components in the HSI color space, it produced visually pleasing underwater images suitable for analysis and interpretation.

2.6 enhancement algorithm based on contourlet transform

Author: Shi et al.

Shi et al. (2010) proposed an enhancement algorithm based on contourlet transform and multi-scale retinex to improve global contrast in underwater images. Decomposing the image using non-subsampled contourlet transform captured multi-scale image features. Applying multi-scale retinex in the low-frequency sub-band enhanced contrast while preserving details. However, challenges in handling images with uneven illumination could affect its effectiveness in real-world underwater scenarios.

2.7 CIELAB color space

Author : Zhang et al.

In 2017, Zhang et al. extended the multi-scale retinex technique to the CIELAB color space and introduced a combination of bilateral and trilateral filters tailored to different color channels based on specific constraints. This method effectively mitigates halo artifacts generation; however, its computational complexity is high due to numerous parameters. Vasamsetti et al. introduced a wavelet-based variational enhancement framework for underwater images. By utilizing wavelet decomposition and a set of energy functionals, they adjusted the approximation coefficients of RGB components to modify the average intensity, and further refined these coefficients at finer scales to correct colors and enhance contrast. Mhala and Pais presented UIE-net, a convolutional neural network (CNN) designed for underwater image enhancement. This network focuses on color correction and haze removal to enhance underwater images. Another model proposed by Sun et al. is based on encoding-decoding deep CNN networks, primarily trained and evaluated using synthetic datasets simulating various noise environments and underwater conditions.

2.8 Color compensation of bright channels and fusion techniques

Author : Dai et al.

Moving to 2018, Dai et al. introduced an enhancement method based on color compensation of bright channels and fusion techniques. Wang et al. proposed an algorithm for deblurring and denoising by utilizing a sparse representation of the dark channel image, resulting in improved entropy and average gradient in underwater images.

2.9 Restoration method based on scene depth estimation

Author : Cai et al.

In 2019, Cai et al. proposed a restoration method based on scene depth estimation and white balance adjustment, which may experience misjudgment in cases with numerous texture features in distant views. Ueda et al. focused on synthesizing underwater images by modeling accurate degradation processes considering absorption, scattering, and various water types.

2.10 UIE benchmark (UIEB) comprising real-world underwater images

Author : Li et al.

In 2020, Li et al. constructed a UIE benchmark (UIEB) comprising real-world underwater images, alongside a gated fusion network called Water-Net serving as a baseline. Marques et al. enhanced contrast, saliency, and color saturation of underwater images by fusing information from two different models, while Li et al. designed a balanced color correction algorithm enhancing contrast and brightness based on prior knowledge of the red channel.

2.11 CNNs to estimate illumination images

Author : Guo et al.

In 2021, Guo et al. utilized CNNs to estimate illumination images, separating them from underwater images to obtain the reflectance image, considered the final enhanced underwater image. Hu et al. proposed a two-branch deep neural network capable of separately removing color cast and enhancing image contrast by leveraging properties of the HSV color space.

2.12 Color compensation method

Author : Gong and Hu

In 2022, Gong and Hu introduced a color compensation method combining Monte Carlo simulation and measured experiments to correct color distortion and improve underwater target visibility. Lastly, in 2023, Kang et al. proposed the SPDF framework for underwater image enhancement, which fuses complementary pre-processed inputs in a perception-aware and conceptually independent image space, offering separate fusion of different components without information loss.

Color correction and contrast stretching techniques are commonly employed to enhance the contrast and partially correct colors in underwater images. However, these methods carry the risk of amplifying noise and introducing artifacts into the image, potentially compromising its quality. Domain transformation methods, while effective in noise reduction, often struggle to address other degradation issues present in underwater images. Dehazing-based methods, although effective, are often computationally intensive, leading to longer processing times. Additionally, optical model-based approaches rely heavily on assumptions and hypotheses that may not accurately represent real-world underwater conditions.

Learning-based methods have shown promise in addressing underwater image enhancement tasks. However, they heavily rely on the availability of comprehensive and representative training data. Consequently, their performance may suffer when faced with underwater scenarios significantly different from the training data.

In addition to these traditional methods, researchers have explored techniques from diverse fields to analyze and improve underwater images. For instance, Abunaser et al. utilized particle swarm optimization to mitigate the effects of light absorption and scattering in underwater images, offering alternative approaches to traditional image enhancement methods. Furthermore, advancements in optical imaging devices, such as laser-scanning underwater imaging and range-gating technology, have contributed to improving the range and clarity of underwater imaging. Despite these technological advancements, image-processing technologies continue to play a crucial role due to their cost-effectiveness, low computational load, and ease of implementation, ensuring their continued relevance in underwater image enhancement.

CHAPTER – III

DIGITAL IMAGE PROCESSING

3.1 Introduction

Digital Image Processing means processing digital image by means of a digital computer. We can also say that it is a use of computer algorithms, in order to get enhanced image either to extract some useful information. Image processing mainly include the following steps

a. Importing the image via image acquisition tools
b. Analyzing and manipulating the image.
c. Output in which result can be altered image or a report, which is based on analyzing that image.

3.1.1 Fundamentals of Digital Image

Image:

An image is a two-dimensional picture, which has a similar appearance to some subject usually a physical object or a person. An image is defined as a two- dimensional function, F(x,y), where x and y are spatial coordinates, and the amplitude of F at any pair of coordinates (x,y) is called the intensity of that image at that point. When x,y, and amplitude values of F are finite, we call it a digital image.

In other words, an image can be defined by a two-dimensional array specifically arranged in rows and columns. Digital Image is composed of a finite number of elements, each of which elements have a particular value at a particular location. These elements are referred to as picture elements, image elements, and pixels. A Pixel is most widely used to denote the elements of a Digital Image.

Classification of Images:

There are three types of images used in Digital Image Processing as follows

A. Binary image

A binary image is a digital image that has only two possible values for each pixel. Typically, the two colors used for a binary image are black and white though any two colors can be used. The color used for the object(s) in the image is the foreground color while the rest of the image is the background color. Binary images are also called bi-level or two-level. This means that each pixel is stored as a single bit (0 or 1). This name black and white, monochrome or monochromatic are often used for this concept, but may also designate any images that have only one sample per pixel, such as grayscale images.

Binary images often arise in digital image processing as masks or as the result of certain operations such as segmentation, thresholding, and dithering. Some input/output devices, such as laser printers, fax machines, and bi-level computer displays, can only handle bi-level images.

B. Gray scale image

A grayscale Image is digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray (0-255), varying from black (0) at the weakest intensity to white (255) at the strongest.

Grayscale images are distinct from one-bit black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white (also called bi-level or binary images). Grayscale images have many shades of gray in between. Grayscale images are also called monochromatic, denoting the absence of any chromatic variation. Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured.

C. Color image

A (digital) color image is a digital image that includes color information for each pixel. Each pixel has a particular value, which determines it is appearing color.

Three numbers giving the decomposition of the color in the three primary colors Red, Green and Blue qualify this value. Any color visible to human eye can be represented this way.

A number between 0 and 255 quantifies the decomposition of a color in the three primary colors. For example, white will be coded as R = 255, G = 255, B = 255; black will be known as (R,G,B) = (0,0,0); and say, bright pink will be : (255,0,255).

In other words, an image is an enormous two-dimensional array of color values, pixels, each of them coded on 3 bytes, representing the three primary colors. This allows the image to contain 256x256x256 = 16.8 million different colors. This technique is also known as RGB encoding and is specifically adapted to human vision

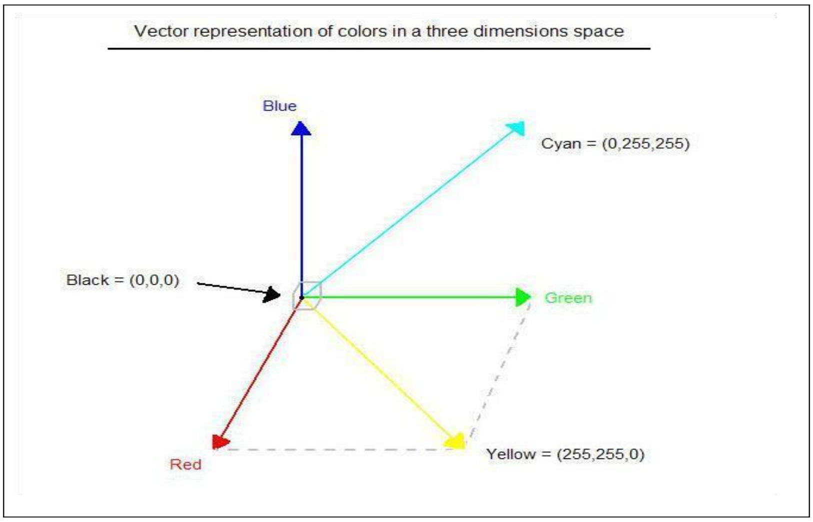

Figure 3.1 Hue saturation process of RGB scale image

From the above Figure 3.1, colors are coded on three bytes representing their decomposition on the three primary colors. It sounds obvious to a mathematician to immediately interpret colors as vectors in a Single Image Dehazing Method Based on Nonlinear Transformation Dept. of three dimension space where each axis stands for one of the primary colors. Therefore, we will benefit of most of the geometric mathematical concepts to deal with our colors, such as norms, scalar product, projection, rotation or distance.

Figure 3.2 Color image to gray scale image conversion

3.1.2 Image processing

Digital image processing, the manipulation of images by computer, is relatively recent development in terms of man's ancient fascination with visual stimuli. In its short history, it has been applied to practically every type of images with varying degree of success.

The inherent subjective appeal of pictorial displays attracts perhaps a disproportionate amount of attention from the scientists and from the nonprofessional. Digital image processing like other glamour fields, suffers from myths, disconnections, misunderstandings and misinformation.

It is vast umbrella under which fall diverse aspect of optics, electronics, mathematics, photography graphics and computer technology. Several factors combine to indicate a lively future for digital image processing. A major factor is the declining cost of computer equipment. Several new technological trends promise to further promote digital image processing. These include parallel processing mode practical by low cost microprocessors, and the use of charge coupled devices (CCDs) for digitizing, storage during processing and display and large low cost of image storage arrays

3.2 Fundamental Steps In Digital Image Processing

3.2.1 Image Acquisition

Image Acquisition is to acquire a digital image. To do so requires an image sensor and the capability to digitize the signal produced by the sensor. The sensor could be monochrome or color TV camera that produces an entire image of the problem domain every 1/30 sec. The image sensor could also be line scan camera that produces a single image line at a time. The below Figure 3.3 shows the digital camera.

Figure 3.3 Digital camera

Scanner produces a two-dimensional image. If the output of the camera or other imaging sensor is not in digital form, an analog to digital converter digitizes it. The nature of the sensor and the image it produces are determined by the application. The below Figure 3.4 shows the basic steps of image processing.

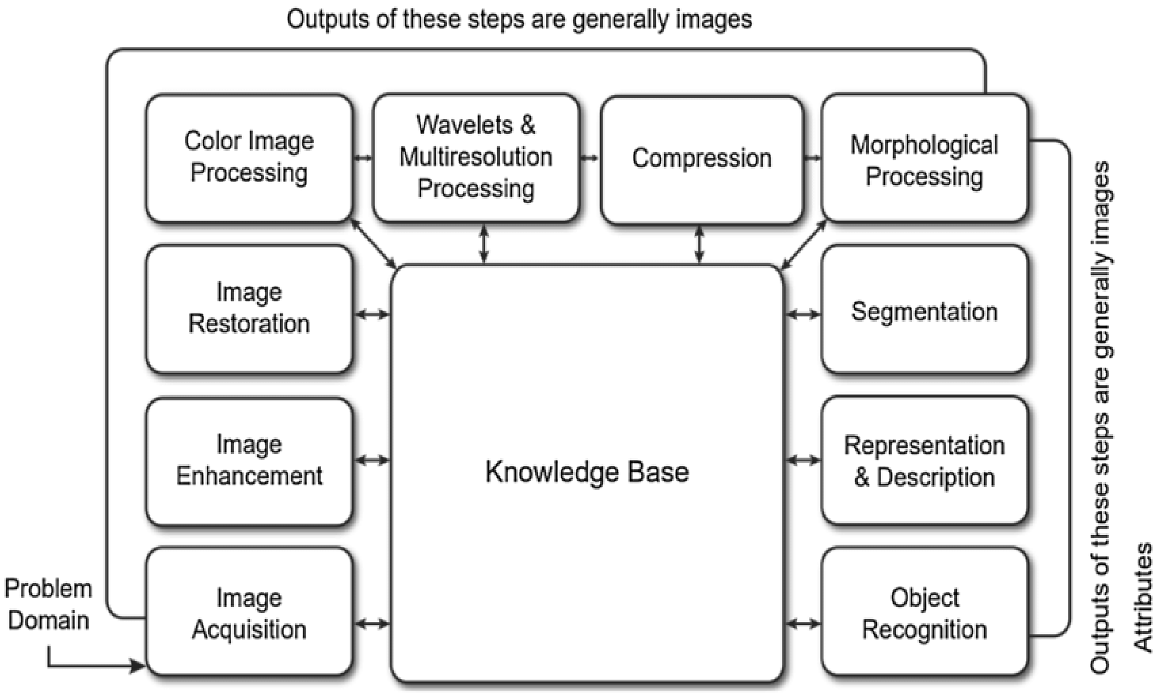

Figure 3.4 Basics of Image Processing

3.2.2 Image Enhancement

Image enhancement is among the simplest and most appealing areas of digital image processing. The idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interesting an image. A familiar example of enhancement is when we increase the contrast of an image because “it looks better.” It is important to keep in mind that enhancement is a very subjective area of image processing.

Figure 3.5 Image Enhancement Process for Gray Scale Image

3.2.3 Image restoration

Image restoration is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation.

Figure 3.6 Noise image to Image Enhancement

3.2.4 Color image processing

The use of color in image processing is motivated by two principal factors. First, color is a powerful descriptor that often simplifies object identification and extraction from a scene. Second, humans can discern thousands of color shades and intensities, compared to about only two dozen shades of gray. This second factor is particularly important in manual image analysis. The gray scale image to color image conversion is shown in Figure 3.7.

Figure 3.7 Gray scale image to color image

3.2.5 Segmentation

Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually. The below Figure 3.8 shows the Image Segment process.

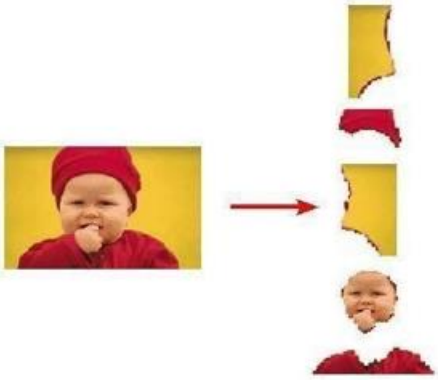

Figure 3.8 Image segment Process

On the other hand, weak or erratic segmentation algorithms usually guarantee eventual failure. In general, the more accurate the segmentation, the more likely recognition is to succeed. Digital image is defined as a two dimensional function f(x, y), where x and y are spatial (plane)coordinates, and the amplitude off at any pair of coordinates (x, y) is called intensity or grey level of the image at that point. The field of digital image processing refers to processing digital images by means of a digital computer. The digital image is composed of a finite number of elements, each of which has a particular location and value. The elements are referred to as picture elements, image elements, pels, and pixels. Pixel is the term most widely used.

3.2.6 Image Compression

Digital Image compression addresses the problem of reducing the amount of data required to represent a digital image. The underlying basis of the reduction process is removal of redundant data. From the mathematical viewpoint, this amounts to transforming a 2D pixel array into a statically uncorrelated data set. The data redundancy is not an abstract concept but a mathematically quantifiable entity. If n1 and n2 denote the number of information-carrying units in two data sets that represent the same information, the relative data redundancy RD of the first data set (the one characterized by n1) can be defined as,

RD = 1-(1/CR)

Where CR called as compression ratio. It is defined as

CR=(η1/η2)

In image compression, three basic data redundancies can be identified and exploited: Coding redundancy, interpixel redundancy, and psychovisual redundancy. Image compression is achieved when one or more of these redundancies are reduced or eliminated. The image compression is mainly used for image transmission and storage. Image transmission applications are in broadcast television; remote sensing via satellite, aircraft, radar, or sonar, teleconferencing and computer communications.

Image storage is required most commonly for educational and business documents, medical images that arise in computer tomography (CT), magnetic resonance imaging (MRI) and digital radiology, motion pictures, satellite images, weather maps, geological surveys, and so on.

Image compression model

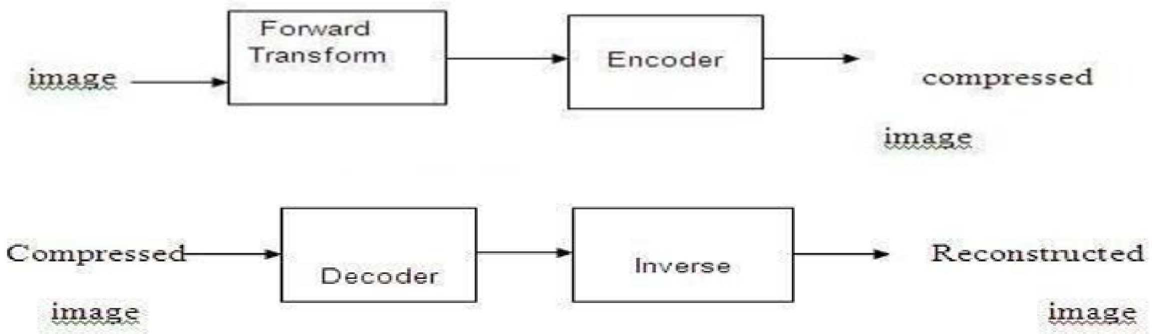

Figure 3.9 Image compression and decompression of image

3.2.7 Wavelets and Multi-Resolution Processing

It is foundation of representing images in various degrees. A scaling function scaling function is used to create a series of approximations of a function or image, each differing by a factor of 2 from its neighboring approximations. ‡ Additional functions called wavelets are then used to encode the difference in information between adjacent approximations.

3.2.8 Morphological Processing

Morphological processing deals with tools for extracting image components that are useful in the representation and description of shape

3.2.9 Representation and Description

Representation and description usually follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region or all the points in the region itself. It follows output of segmentation stage, choosing a representation is only the part of solution for transforming raw data into processed data. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. Description deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another.

3.2.10 Object Recognition

Recognition is the process that assigns a label, such as, “vehicle” to an object based on its descriptors.

3.2.11 Knowledge Base

Knowledge may be as simple as detailing regions of an image where the information of interest is known to be located, thus limiting the search that has to be conducted in seeking that information. The knowledge base also can be quite complex, such as an interrelated list of all major possible defects in a materials inspection problem or an image database containing high resolution satellite images of a region in connection with change detection applications.

3.3 Summary

Image processing concepts and basic block diagram of image processing have been discussed in this chapter. It provides basic information about image processing concepts for doing the project

CHAPTER - IV

Existing Method

4.1 Introduction:

Underwater imaging faces significant challenges due to the absorption and scattering effects of light in water, resulting in color bias and low contrast in captured images. These degraded images often struggle to meet the requirements for effective underwater operations, hindering tasks such as marine exploration, environmental monitoring, and underwater resource management. Traditional methods for underwater image restoration and enhancement have been developed to mitigate these challenges. However, these methods typically require lengthy computation times and frequently produce unsatisfactory result. The limitations of these traditional approaches underscore the need for innovative solutions capable of overcoming these drawbacks and improving the quality of underwater images.

In the study, they proposed a novel approach to underwater image restoration that addresses these challenges. Our method involves background light estimation based on double-opponency and transmission estimation utilizing the red channel prior. By mimicking human visual color constancy and leveraging prior knowledge about light propagation in water, our approach aims to accurately restore underwater images while reducing computational overhead. Furthermore, to enhance the contrast effect and overall visual quality of the restored images, we incorporate a fusion process with contrast stretch processing conducted in the HSV color space. This fusion process amplifies contrast effects, resulting in final output images with improved clarity and color fidelity. Experimental results demonstrate the effectiveness of our proposed method, showcasing a significant reduction in computation time compared to conventional methods while producing clearer and more natural color images. Both objective metrics and subjective evaluations support the efficacy of our approach, highlighting its potential to address the challenges associated with underwater image restoration and enhancement.

4.2 Methodology:

In the conventional optical imaging model for underwater scenarios, the acquired underwater image I is composed of three primary factors: the direct component (ID), representing light reflected by objects; the forward scattering component (IFS), indicating the deviation of light from its original propagation direction; and the backward scattering component (IBS), which accounts for light reflections caused by particles between objects and the imaging equipment. This model can be expressed as:

$$\boldsymbol{I} = \boldsymbol{I_D} + \boldsymbol{I_{FS}} + \boldsymbol{I_{BS}}$$

Research has shown that the main contributors to image degradation are ID and IBS, thus making IFS negligible. Expressing ID and IBS as functions of scene radiance (J) and background light (E) respectively, we have:

ID = JT

IBS = E(1-t)

In Equation, x denotes the pixel coordinate and c represents the color channel. I c is the acquired input image value for color channel c, Jc is the object image to be restored, t c denotes the transmission for color channel c, and Ec represents the background light for color channel c.

In the subsequent sections, a novel method for enhancing underwater images is introduced. This method employs two distinct processes: one for estimating the background light (Ec) and transmission (tc), addressing major degradation issues; and the other for contrast stretching. The outputs of these processes are then fused in the hue, saturation, and value (HSV) color space to produce the final enhanced image.

4.3 Existing Methods for Transmission Estimation:

4.3.1 Dark Channel Prior:

The Dark Channel Prior (DCP) is a sophisticated technique used in image processing, initially developed to address haze in outdoor images but later adapted for underwater imaging. At its core, DCP relies on a crucial observation about natural images within local regions of an image, there are usually pixels that appear very dark in at least one color channel. This phenomenon is termed the "dark channel" and serves as the cornerstone of the DCP methodology.

In the context of underwater imaging, where water turbidity causes light attenuation and reduces visibility, the concept of haze in outdoor scenes can be likened to the degradation caused by underwater conditions. Here, the dark channel helps estimate the transmission of light through the water. Transmission refers to the proportion of light that manages to pass through the medium without being scattered or absorbed. Higher transmission values indicate clearer regions with less attenuation, while lower values indicate hazier areas with more attenuation.

To estimate transmission using DCP, the algorithm examines local patches within the underwater image. Within each patch, it identifies the minimum intensity value across color channels, which constitutes the dark channel. By analyzing the statistical properties of the dark channel, such as its percentile value, the algorithm derives an estimate of transmission for each patch.

Once transmission is estimated for each patch, it can be leveraged for various image enhancement tasks, such as dehazing or restoration. By incorporating the estimated transmission into a dehazing algorithm, the algorithm can effectively mitigate the effects of water attenuation and improve underwater visibility. This results in clearer and more visually appealing underwater images, aiding applications ranging from scientific research to underwater photography and filmmaking.

The Dark Channel Prior (DCP) method, while powerful for transmission estimation and image enhancement, encounters several challenges. Firstly, its assumption of uniform atmospheric light across the entire image may not always hold true, especially in scenes with varying lighting conditions or complex atmospheric effects. This can lead to inaccurate transmission estimates, particularly in areas with high contrast or thin structures. Additionally, the method's sensitivity to scene content means that it may struggle with scenes lacking sufficient contrast or containing homogeneous regions, potentially resulting in unreliable transmission estimates.

Furthermore, inaccuracies can arise due to noise, outliers, and deviations from the underlying assumptions of the DCP framework, leading to artifacts in the enhanced images.

Moreover, the adaptability of the DCP method to different environments, including underwater imaging, is limited. Variations in water clarity, depth, and ambient lighting can impact the reliability and accuracy of transmission estimates obtained using DCP. Additionally, implementing the DCP method can be computationally intensive, particularly for large-scale or high-resolution images, which may restrict its applicability in real-time or resource-constrained scenarios. While DCP offers valuable capabilities, addressing its limitations and combining it with complementary techniques can enhance its effectiveness and robustness in various applications, ensuring more accurate transmission estimation and image enhancement.

4.2.2 Red Channel Prior:

The Red Channel Prior (RCP) method, while innovative for transmission estimation in underwater imaging, faces certain limitations. Firstly, it relies on the assumption that red light is attenuated more rapidly than other colors underwater, making it a suitable indicator of water turbidity. However, this assumption may not always hold true in all underwater environments, particularly in scenarios where water conditions vary or artificial lighting sources introduce complexities. Consequently, the accuracy of transmission estimates derived from the RCP method can be affected, leading to potential inaccuracies in the enhanced images. Furthermore, the RCP method may encounter challenges in accurately estimating transmission in regions with diverse content or complex color distributions. Variations in scene illumination, object colors, and underwater structures can impact the reliability of transmission estimates obtained from the red channel analysis. Additionally, similar to other transmission estimation techniques, the RCP method may struggle with thin structures or regions lacking sufficient contrast, potentially leading to artifacts in the final enhanced images. Despite these limitations, the RCP method provides valuable insights into underwater visibility and can serve as a useful tool for image enhancement. By addressing its shortcomings and integrating it with complementary techniques, researchers can enhance its effectiveness and applicability in various underwater imaging applications.

The Red Channel Prior (RCP) method, while effective for estimating transmission in underwater imaging, faces several challenges. Firstly, it relies on the assumption that red light attenuates more rapidly than other colors underwater, serving as an indicator of water turbidity. However, this assumption may not hold true universally, especially in environments with varying water conditions or artificial lighting sources. Consequently, the accuracy of transmission estimates derived from RCP may be compromised, leading to potential inaccuracies in the resulting enhanced images.

CHAPTER – V

Proposed Method

5.1 Introduction

Underwater imaging faces significant challenges due to the absorption and scattering effects of light in water, leading to color bias and low contrast in captured images. These degraded images often fall short of meeting the requirements for effective underwater operations. Traditional methods for restoring and enhancing underwater images typically involve lengthy computation times and often yield unsatisfactory results. In this study, a novel approach to underwater image restoration is proposed, which involves background light estimation based on double-opponency and transmission estimation utilizing the red channel prior. Background light estimation is achieved through double-opponency, mimicking human visual color constancy to obtain background light information consistent with human perception. Transmission estimation leverages prior knowledge that red wavelengths experience the fastest attenuation in water.

To further enhance contrast in the restored image, it is fused with the output of contrast stretch processing conducted in the HSV color space. This fusion process aims to amplify contrast effects, resulting in a final output image with improved clarity and color fidelity. Experimental results demonstrate that the proposed method significantly reduces computation time by 40% or more compared to conventional methods. Moreover, both objective metrics and subjective evaluations indicate that the proposed approach produces clearer and more natural color images, effectively addressing the challenges associated with underwater image restoration and enhancement.

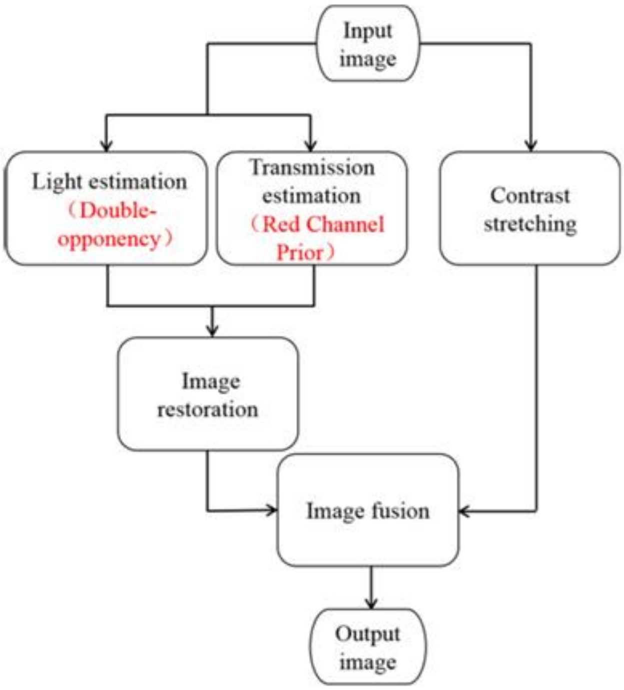

Figure 5.1 Flow diagram of the proposed method

In the classic optical imaging model, an underwater image captured by underwater equipment can be understood as a combination of three main factors: the direct component (ID), which represents the light reflected by the object; the forward scattering component (IFS), indicating how light deviates from its original path; and the backward scattering component (IBS), representing the reflection of particles between the object and the equipment. Research suggests that most degradation in underwater images is primarily caused by the direct component (ID) and the backward scattering component (IBS), making the contribution of the forward scattering component (IFS) negligible.

The direct component (ID) and the backward scattering component (IBS) can be defined as follows: ID refers to the scene radiance of the non-degraded image, while IBS represents the background light. The transmission factor (t) signifies the degree to which light passes through the water medium. Therefore, the degradation model for underwater images can be expressed as follows. The acquired input image value (Ic) of each color channel (c) is a combination of the object image to be restored (Jc), multiplied by the transmission factor (tc), and the background light (Ec) multiplied by the complementary transmission factor (1 − tc). In the proposed method for clarifying underwater images, two independent processes are employed. One process focuses on estimating the values of the background light (Ec) and the transmission factor (tc) to address major degradation issues, while the other process involves contrast stretching. Subsequently, the outputs of these two processes are fused in the hue, saturation, value (HSV) color space to obtain the final output image.

A flow diagram illustrating the proposed method is depicted in Figure 1, with detailed explanations provided in the following subsections.

5.2 Double-Opponency based Color Constancy Mode

Human color perception relies on a sophisticated neural mechanism that enables us to accurately perceive the colors of objects even under varying lighting conditions. At the heart of this mechanism are the double-opponency (DO) color-sensing cells located in the primary visual cortex of the human brain. These cells play a pivotal role in maintaining stable color perception by effectively filtering out the effects of different lighting conditions.

Researchers, led by Gao et al., have conducted studies demonstrating the remarkable response consistency of DO cells to images with color biases. They found that the distribution of responses from DO cells closely matches the vector representing the color of the light source in the scene. Building upon this discovery, they developed a computational model known as the color constancy model, which efficiently estimates the color of the light source in a given scene. Notably, this model relies heavily on linear calculations, making it computationally efficient and practical for real-world applications. To understand how this color constancy mechanism operates in the human visual system, it's crucial to delve into the hierarchical process of color perception. Initially, visual input is received by the retina, where light-sensitive cells convert it into neural signals. These signals are then transmitted through the lateral geniculate nucleus (LGN) of the thalamus to reach the primary visual cortex (V1) and other advanced visual areas.

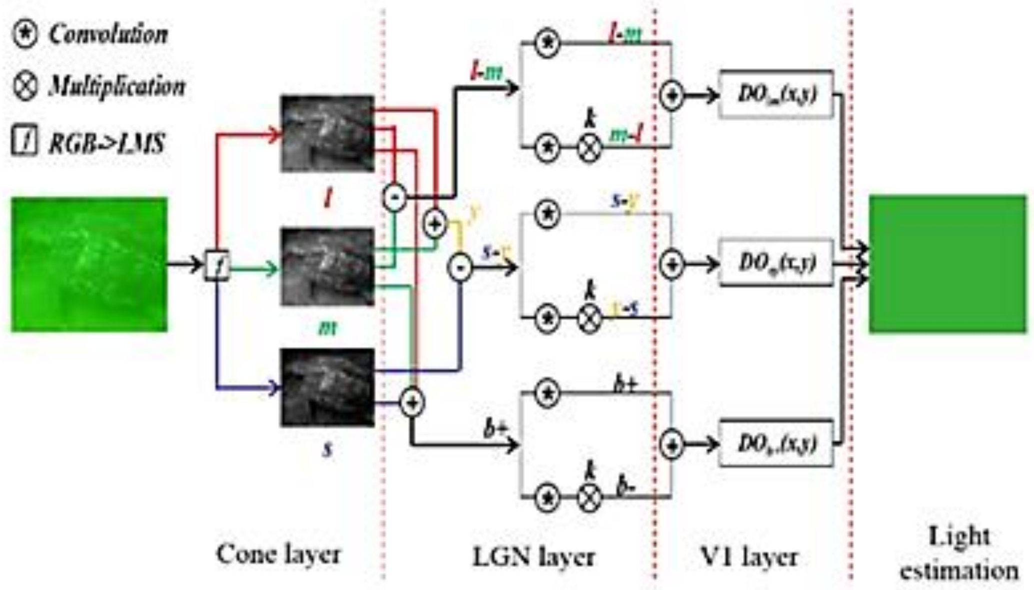

Figure 5.2 Light estimation

The computational model inspired by the neural mechanisms of color processing in the early visual stages is termed the double-opponency-based color constancy (DOCC) model. In this model, the input image undergoes a transformation from the RGB color space to the LMS color space. This transformation simulates the responses of cone cells in the retina, which are sensitive to long-wavelength (L), medium-wavelength (M), and short-wavelength (S) light, corresponding to red (R), green (G), and blue (B) colors, respectively.

Subsequently, color information is encoded using single-opponent (SO) and double-opponent (DO) cells. DO cells, predominantly found in the primary visual cortex (V1), play a crucial role in detecting local color contrast within receptive fields (RF) through spatial transformations. This mechanism aids in achieving color constancy by effectively normalizing perceived colors under different lighting conditions.

Finally, the color-coded information undergoes further processing and analysis in the higher visual cortex, where it is transformed into the trichromatic space (red, green, and blue). This hierarchical processing pathway ensures that humans perceive consistent and accurate colors despite variations in lighting conditions, thereby highlighting the remarkable adaptability and efficiency of the human visual system.

At the core of our method lies the intricate process of estimating underwater light utilizing the Double-Opponency Color Constancy (DOCC) model, which is depicted in a schematic form in Figure 2.

5.3 LMS Spatial Expression of Cone Cells

In the initial phase, akin to how the L, M, and S cones of the retina encode visual information received by the eye, we transition the image from the RGB color space to the LMS spatial expression of cone cells. This transformation is facilitated through the XYZ colo r space, adhering to the defined relationship between the RGB and LMS color spaces according to the International Telecommunication Union's standards. This transformation is encapsulated in a transformation matrix.

According to the standard issued by the International Telecommunication Union, the relationship between the RGB and LMS color spaces can be expressed as follows

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3192 & 0.6089 & 0.0447 \\ 0.1647 & 0.7638 & 0.0870 \\ 0.0202 & 0.1295 & 0.9391 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

5.4 Single-Opponency response in lgn layer

Following the conversion to the LMS spatial expression, the next step involves the conversion of spatial information into single opponency (O) within the LGN (lateral geniculate nucleus) layer. This single opponency response, denoted as Olm, Oys, and Ob+ and Ob-, pertains to different color channels and is achieved through a transformation operation and subsequent Gaussian convolution. The convolution process calculates the response of receptive fields, termed as Single-Opponent (SO), which are crucial in encoding color contrasts.

$$\left\{ \begin{array}{c} \begin{bmatrix} \mathrm{Olm} \\ \mathrm{Oys} \\ \mathrm{Ob+} \end{bmatrix} = Tran.* \begin{bmatrix} \mathrm{L} \\ \mathrm{M} \\ \mathrm{S} \end{bmatrix}, \begin{bmatrix} \mathrm{Oml} \\ \mathrm{Osy} \\ \mathrm{Ob-} \end{bmatrix} = - \begin{bmatrix} \mathrm{Olm} \\ \mathrm{Oys} \\ \mathrm{Ob+} \end{bmatrix} \\ Tran. = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & \frac{-2}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \end{array} \right\}$$

According to above equation the spatial information of LMS is transformed into single opponency (denoted as O).

5.5 Double-Opponency in V1 Layer

Transitioning into the V1 cortex, a pivotal stage is reached where two single-opponent responses, each with distinct receptive field sizes, synergize to form a double-opponency response (DO). This response, computed for each color channel, is intricately influenced by the size and weight of both center and surrounding receptive fields. The parameter k delineates the weight of the surrounding receptive field, offering control over its influence. When k is set to 0, the effect of the surrounding receptive field is effectively discounted, emphasizing the significance of the center receptive field in the computation. This intricate interplay of receptive fields within the V1 cortex underscores the complexity and sophistication of the neural processes involved in underwater light estimation through the DOCC model.

In the V1 cortex, two single opponents with different receptive field sizes work together to form a double-opponency response (DO), given by formula

$$DO_{lm}(x, y) = SO_{l+m-}(x, y; \sigma) + k \cdot SO_{m+l-}(x, y; \lambda\sigma)$$

$$DO_{sy}(x, y) = SO_{s+y-}(x, y; \sigma) + k \cdot SO_{y+s-}(x, y; \lambda\sigma)$$

$$DO_{b+}(x, y) = SO_{b+}(x, y; \sigma) + k \cdot SO_{b-}(x, y; \lambda\sigma)$$

In the above formula, σ defines the size of centre receptive field, and λσ defines the size of the surrounding receptive field which in general, is three times that of the central receptive field, i.e. $\lambda = 3$. The parameter $k \in [0, 1)$ denotes the weight of the surrounding receptive field. When $k = 0$, the effect of surrounding receptive field is ignored.

5.6 Color Sensing in Higher Visual Cortex

Upon reaching the higher-level visual cortex, the signals are reprocessed back into the LMS color space to extract color information. This step simulates the hierarchical process of human visual perception, where the brain interprets signals received from the retina. In this stage, the model assumes that the scene is illuminated by a single light source with uniform

color distribution across the scene. Consequently, the color of the background light is estimated based on the signals processed in the visual cortex.
To achieve this, the model employs a computational process inspired by the principles of human color perception. The estimated background light information is then transformed into the RGB color space for display and further analysis.

According to the below equation, the signals are transferred back to LMS space to obtain color information in High-level visual cortex.

$$\begin{bmatrix} DT_l \\ DT_m \\ DT_s \end{bmatrix} = \text{Tran.}^{-1} * \begin{bmatrix} DO_{lm} \\ DO_{sy} \\ DO_{b+} \end{bmatrix}$$

Assuming the that the scene is illuminated by a single light source with a spatially uniform color across the scene. Finally, the color of the background light, Elms= (El, Em, Es), is estimated as follows:

$$\{E_i = \max(DT_i) \,/ \sum_{\max(DT_i)} f \quad i \in \{l, m, s\}$$

$$\{\sum f = \sum_{i \in \{l,m,s\}} \max(DT_i)$$

It is necessary to transfer the E_{lms} in LMS space to E_{rgb} in RGB space, for display and subsequent use. The corresponding transformation matrix is given by,

$$E_{rgb} = \begin{bmatrix} E_R \\ E_G \\ E_B \end{bmatrix} = \begin{bmatrix} 5.3341 & -4.2829 & 0.1428 \\ -1.1556 & 2.2581 & -0.1542 \\ 0.0448 & -0.2195 & 1.0831 \end{bmatrix} \begin{bmatrix} E_l \\ E_m \\ E_s \end{bmatrix}$$

5.7 Transmission Estimation Based on Green Channel Prior

In underwater environments, different colors experience varying rates of attenuation as distance increases, with red wavelengths being more affected. To address this, researchers have modified the dark channel prior and introduced the red channel prior. The red channel prior is a method to estimate the transmission of light through water, which is crucial for restoring underwater images.

Moreover, the RCP method may struggle with accurately estimating transmission in regions with diverse content or complex color distributions.

Variations in scene illumination, object colors, and underwater structures can affect the reliability of transmission estimates obtained through red channel analysis. Additionally, like other transmission estimation techniques, RCP may encounter difficulties in handling thin structures or regions lacking sufficient contrast, potentially resulting in artifacts in the final enhanced images. Despite these challenges, RCP offers valuable insights into underwater visibility and can be a useful tool for image enhancement. Addressing its limitations and integrating it with complementary techniques can enhance its effectiveness and applicability in various underwater imaging scenarios.

We introduce the Green Channel Prior (GCP), this innovative method for transmission estimation in underwater imaging diverges from traditional approaches by leveraging the green color channel instead of the red channel. While the Red Channel Prior (RCP) method focuses solely on the attenuation of red light, which can be heavily influenced by water conditions and artificial lighting, GCP offers a more comprehensive and robust solution. By considering the green channel, GCP takes advantage of the fact that green light experiences less absorption and scattering in water compared to red light, making it a more reliable indicator of underwater visibility. This broader scope allows GCP to provide accurate transmission estimates across a wide range of underwater environments, including those with varying water conditions and artificial lighting sources.

$$\boldsymbol{min}\left(\min_{y\in\Omega(x)}\left(\mathbf{1}-\boldsymbol{J_G}(\boldsymbol{y})\right),\min_{y\in\Omega(x)}\left(\boldsymbol{J_R}(\boldsymbol{y})\right),\min_{y\in\Omega(x)}\left(\boldsymbol{J_B}(\boldsymbol{y})\right)\right)\approx\mathbf{0}$$

In the literature, Galdran et al. deduced the transmission in detail based on Green-channel prior, whereby the transmission of tc(x) is estimated by Equation:

$$\left\{\begin{array}{c} t_G(x) = 1 - min\left(\dfrac{\min_{y\in\Omega(x)}\left(\mathbf{1}-\boldsymbol{I_G}(\boldsymbol{y})\right)}{1-E_R},\quad \dfrac{\min_{y\in\Omega(x)}\left(\boldsymbol{I_R}(\boldsymbol{y})\right)}{E_R},\quad \dfrac{\min_{y\in\Omega(x)}\left(\boldsymbol{I_B}(\boldsymbol{y})\right)}{E_B}\right) \\ t_R(x) = t_G(x)^{\lambda_R} \\ t_B(x) = t_G(x)^{\lambda_B} \end{array}\right\}$$

In contrast to RCP, GCP offers several key advantages that make it a superior choice for transmission estimation and image enhancement in underwater imaging. Firstly, GCP is less sensitive to variations in water conditions such as turbidity and color, thanks to its reliance on the green channel, which experiences less absorption and scattering in water. Additionally, GCP handles artificial lighting more effectively by mitigating potential inaccuracies introduced by variations in light color temperature, which can affect the reliability of transmission estimates based on the red channel. Moreover, GCP offers enhanced contrast and detail in underwater scenes where the red channel may lack sufficient information, leading to more accurate transmission estimates and visually appealing image enhancements. Overall, the Green Channel Prior method presents a comprehensive and robust approach to transmission estimation in underwater imaging, offering numerous advantages over traditional methods such as the Red Channel Prior approach.

5.8 Final Image Restoration

Using the estimate background light and transmission coefficients, a simplified formula is applied to restore the underwater image. This formula adjusts the intensity values of each color channel based on the transmission coefficient and background light estimation.

By subtracting the estimated background light from the original intensity values and applying a correction factor based on the transmission coefficient, the image is restored to minimize the effects of underwater degradation. The restoration process ensures that the colors are accurately represented and the contrast is enhanced, resulting in a clearer and more visually appealing image.

Overall, the combination of transmission estimation based on the red channel prior and final image restoration yields significant improvements in the clarity and quality of underwater images, as depicted in the results presented.

The results of this computational process closely resemble human visual perceptions, as confirmed by subjective evaluation. This demonstrates the effectiveness of the model in accurately estimating underwater light conditions without relying on complex mathematical formulas.

Based on the E_{rgb} estimation of background light and transmittance t(x) calculated directly, a simplified formula for image restoration is given as,

$$\{J_R(x) = \frac{I_R(x) - E_R(x)}{\max(t(x), t_0)} + (1 - E_R(x))E_R(x)$$

$$\{J_G(x) = \frac{I_G(x) - E_G(x)}{\max(t(x), t_0)} + (1 - E_G(x))E_G(x)$$

$$\{J_B(x) = \frac{I_B(x) - E_B(x)}{\max(t(x), t_0)} + (1 - E_B(x))E_B(x)$$

In the above formula t_0 is a small value that prevents the denominator from being too small; a typical value of t_0 is 0.1.

5.9 Contrast Stretching

Contrast stretching is also called contrast normalization or contrast enhancement and is a method used to improve the visual quality of an image by broadening the range of intensity values of pixels in it. By doing this, we can enhance the perceived contrast between various objects or characteristics shown in the image. Making details more prominent and enhancing overall quality are therefore two facets that fall under the goal of contrast stretching. It is particularly helpful for images which have low contrast where there is little variation in pixel intensity values throughout it. For instance, every 8-bit grayscale pixel contains a number between zero and 255 inclusively that shows its intensity value. The intensities of all pixels in a digital picture range from 0 to 255 (for an 8-bit grayscale image), with 0 being black and 255 being white Before applying stretch limits to an image, one must first study its histogram The histogram represents the distribution of pixel intensity values in an image; darker values usually appear on the left side while brighter ones appear on the right side

When applying contrast stretching to an image, the modification of the pixel intensity values is executed with the help of the appropriate stretch technique. This can be done for the whole picture or for certain parts that you are interested in depending on specific purposes.

Contrast stretching is a foundational image enhancement technique aimed at improving the visual quality of images by adjusting the distribution of pixel values across the brightness spectrum. It is particularly beneficial in scenarios where images suffer from low contrast, which refers to a limited variation between the darkest and brightest areas, resulting in a flat or dull appearance.

Firstly, the histogram of the image is analyzed to understand the distribution of pixel values. This histogram provides crucial insights into the brightness levels present in the image and helps identify areas of low contrast.

Following histogram analysis, the minimum and maximum pixel values in the image are determined. These values represent the darkest and brightest pixels in the image, respectively.

Subsequently, the pixel values are normalized to a new range, often spanning from 0 to 255 in the case of 8-bit images. This normalization process ensures that all pixel values fall within a consistent and standardized range, facilitating uniform processing.

Next, the pixel values within the original range (determined by the minimum and maximum values) are linearly mapped to the new range. This linear mapping expands the dynamic range of pixel values, effectively stretching the contrast.

A stretching function is then applied to each pixel value to transform it according to the linear mapping. This function redistributes the pixel values while preserving their relative intensities, thereby enhancing contrast.

Finally, the contrast-stretched image is visualized, revealing enhanced brightness, improved contrast, and more vibrant colors compared to the original image. It's important to note that while contrast stretching can significantly enhance the visual appearance of images, care must be taken to strike a balance during the stretching process to avoid introducing artifacts or over-amplifying noise in the image. Various algorithms and methods exist for contrast stretching, each with its own advantages and considerations depending on the specific characteristics of the images being processed.

Underwater images often suffer from low contrast due to the scattering effect of suspended particles in water. To address this issue and enhance the visual quality of the images, contrast stretching is applied. This technique adjusts the distribution of pixel values to improve the overall brightness, contrast, and color richness of the image.

The process of contrast stretching begins by calculating histograms of the red (R), green (G), and blue (B) color channels of the original image. Next, a small proportion of pixel values close to 0 or 255, typically 2% of the total pixels, are disregarded to eliminate extreme values. Then, the minimum (Vmin) and maximum (Vmax) pixel values of the remaining pixels are determined. Finally, the pixel values within the range [Vmin, Vmax] are linearly mapped to the range [0, 255] using a simple equation. This mapping expands the range of pixel values, effectively stretching the contrast and enhancing the overall visual appeal of the image.

While contrast stretching improves the brightness, contrast, and color richness of the underwater images, it may introduce adverse edge effects. These effects can be observed as unwanted artifacts along the edges of objects in the image, as illustrated in Fig. 6. Despite this drawback, contrast stretching remains a valuable technique for enhancing underwater images and making them more visually appealing.

In the previous steps, we obtained two key images: a restoration image (RI) and a contrast-stretched image (LS). These images are pivotal in addressing different aspects of underwater image degradation. The restoration image (RI) primarily tackles the impact of light absorption in water on pixel color, while the contrast-stretched image (LS) focuses on mitigating the effects of light scattering, thereby enhancing pixel intensity. To achieve a comprehensive enhancement, we fuse the improved components of both images.

5.10 Fusion:

Image fusion refers to the process of integrating details from several images of a similar view into a single image. This procedure is aimed at creating a more informative, visually appealing or easier-to-analyze representation. Multiple pictures of the same scene can be captured using various sensors, modalities or imaging techniques. These cameras, satellites and other imaging devices capture these images.

The images may go through some pre-processing steps such as noise reduction, geometric correction, color balancing among others before fusion. This will improve their quality and guarantee uniformity throughout the pictures. Due to dissimilar spatial resolutions, orientations or scales in the input images; they need to be properly aligned with each other via registration which ensures that corresponding features are aligned in space.

Relevant features or information are extracted from each input image. Depending on what the application demands for these could include edges-textures- colors respectively for example. There are different types of fusion techniques applicable for different kinds of application and input data. Common fusion techniques include pixel-level fusion, transform-based fusion, feature-level fusion and decision-level fusion among others.

Firstly, both the restoration image (RI) and the contrast-stretched image (LS) are transformed from the RGB color space to the HSV color space. This transformation allows us to work with the individual components of hue, saturation, and value, facilitating more nuanced manipulation.

Finally, the fused image (RH) in the HSV color space is transformed back to the RGB color space to yield the final output image. This ensures that the resultant image retains the improved color information from the restoration process and the enhanced intensity from the contrast-stretching operation, resulting in a visually enhanced output.

o image enhancement involves a multi-faceted approach to address various forms of degradation caused by light absorption and scattering in water. One crucial step in this process is restoring the original colors of objects submerged underwater. To achieve this, a restoration image (RI) is generated, primarily focusing on correcting color distortions induced by light absorption.

This step is crucial as it ensures that the colors of underwater objects appear as they would in a non-aqueous environment, facilitating better visual perception and object recognition. Simultaneously, the scattering of light in water can lead to reduced contrast and intensity in underwater images. To counteract this effect, a contrast-stretching operation is performed to enhance pixel intensity. The contrast-stretched image (LS) primarily targets the restoration of image brightness and contrast, improving visibility and overall image quality. This step is essential for revealing details that may be obscured by the scattering of light, thereby improving the overall clarity of the underwater scene.

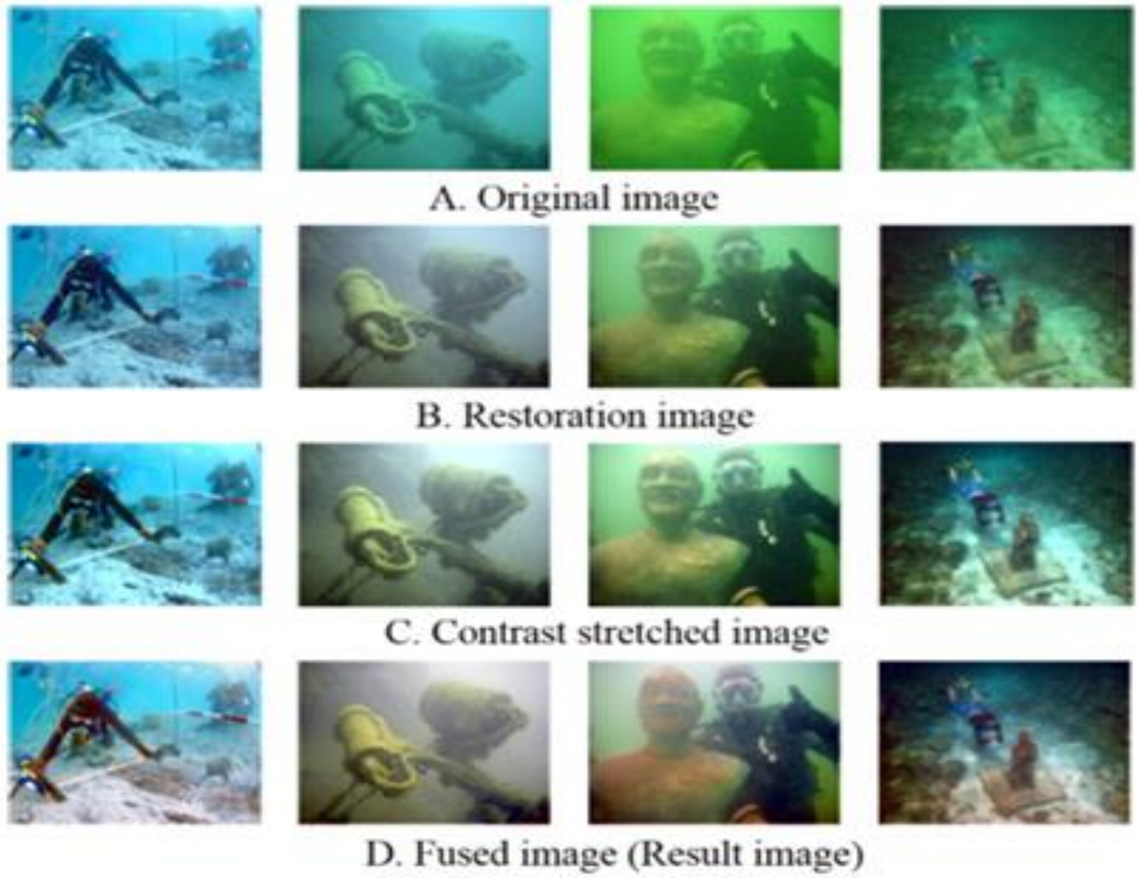

Figure 5.3 Output at each stage

Following the generation of the restoration image (RI) and contrast-stretched image (LS), the next crucial step is to fuse the enhanced components of both images to achieve a comprehensive enhancement. This fusion process aims to leverage the strengths of each image while mitigating their respective weaknesses. By combining the improved color information from the restoration process with the enhanced intensity from the contrast-stretching operation, the fused image (RH) achieves a balanced enhancement, resulting in a visually appealing output.

To facilitate the fusion process, the HSV color space is chosen due to its suitability for manipulating hue, saturation, and value independently. This transformation allows for more nuanced adjustments and precise control over the fusion process. By mapping the hue and saturation components from the restoration image (RI) to the fused image (RH) and the value component from the contrast-stretched image (LS) to RH, the fusion process ensures a harmonious blend of color and intensity enhancements.

After the fusion of the enhanced components, the fused image (RH) is transformed back to the RGB color space to obtain the final output image. This transformation ensures that the resultant image maintains compatibility with standard image viewing and processing tools while retaining the benefits of the fusion process. The final output image represents a comprehensive enhancement of the original underwater scene, combining improved color fidelity, enhanced contrast, and increased visibility.

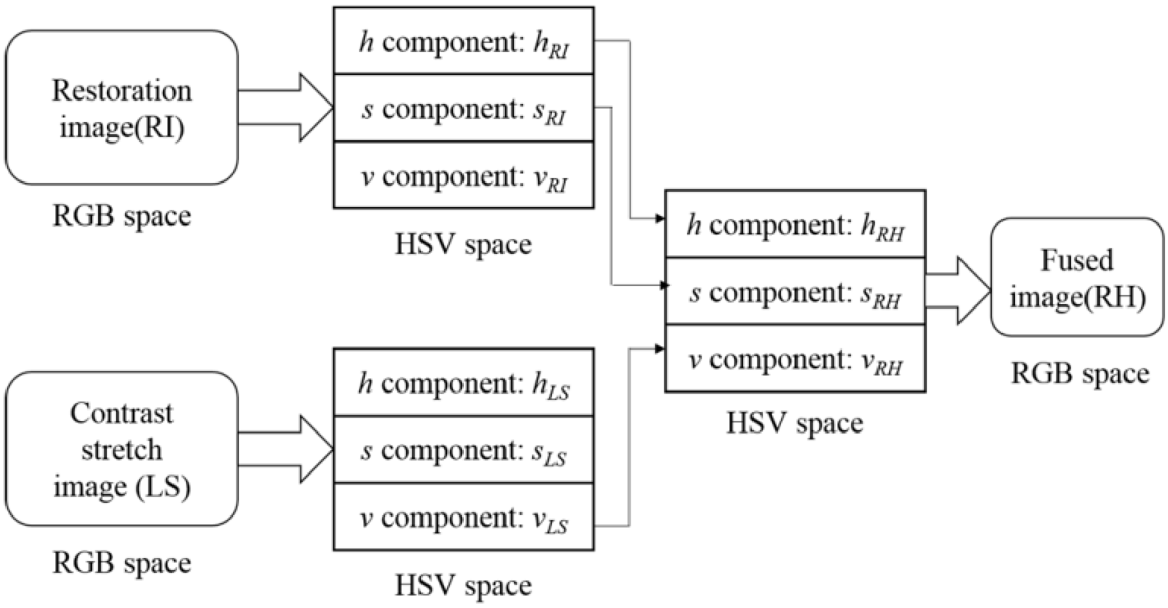

Figure 5.4 Block diagram of Fusion model

Sample images illustrating the efficacy of the proposed method demonstrate the significant improvements achieved through the restoration, contrast-stretching, and fusion processes. These images serve as visual evidence of the method's effectiveness in enhancing underwater images, making them clearer, more vibrant, and easier to interpret. The comprehensive approach employed in this method addresses various aspects of underwater image degradation, resulting in a visually appealing final output that accurately represents the underwater environment.

CHAPTER – VI

6.1 Software Tools

MATLAB is therefore built on a foundation of sophisticated matrix in which the basic element in matrix that does not require pre dimensioning which to solve many technical computing problems especially those with matrix and vector formulations, in a fraction of time.

MATLAB features of applications specific solutions called toolbox. Very important to most users of MATLAB, toolboxes allow learning and applying specialized technology. These are comprehensive collections of MATLAB functions that extend the Areas in which toolboxes are available include signal processing, control system, neural networks, fuzzy logic, wavelets, simulation and many others.

6.1.1 Typical uses of MATLAB

The typical using areas of MATLAB are

1. Math and computation
2. Algorithm and development
3. Data acquisition
4. Data analysis, exploration and visualization
5. Scientific and engineering graphics
6. Modelling
7. Simulation
8. Prototyping

Application development and including graphical user interface building.

MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non-interactive language such as C or FORTRON. MATLAB features a family of add-on application-specific solutions called toolbox.

Very important to most users of MATLAB, toolbox allows you to learn and apply specialized technology. Toolbox is comprehensive collections of MATLAB functions that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation and many others.

6.1.2 Features of MATLAB

1. Advance algorithm for high performance numerical computation, especially in the field matrix algebra.
2. A large collection of predefined mathematical functions and the ability to define one's own functions.
3. Two- and three-dimensional graphics for plotting and displaying data.
4. Powerful, matrix or vector oriented high-level programming language for individual applications.
5. Powerful, matrix or vector oriented high-level programming language for individual applications.
6. Toolboxes available for solving advanced problems in several application areas.

6.1.3 Basic Building Blocks of MATLAB

The basic building block of MATLAB is matrix. The fundamental data type is the array. Vectors, scalars, real matrices and complex matrix are handled as specific class of this basic data type. The built-in functions are optimized for vectors operations. No dimension statements are requiring for vectors of arrays.

6.1.4 MATLAB Window

The MATLAB works based on seven windows

- Command window
- Work space window
- Current directory window
- Command history window
- Editor window
- Graphics window
- Online-help window

Command window

The command window is where the user types MATLAB commands and expressions at the prompt (>>) and where the output of those commands is displayed. It is opened when the application program is launched. All commands including user- written programs are typed in this window at MATLAB prompt for execution.

Work space window

MATLAB defines the workspace as the set of variables that the user creates in a work session. The workspace browser shows these variables and some information about them. Double clicking on a variable in the work space browser launches the array editor, which can be used to obtain information.

Current Directory Window

The current directory tab shows the contents of the current directory, whose path is shown in the current directory window. For example, in the windows operating system the path might be as follows: c\MATLAB\work, indicating that directory "work" is a sub directory of the main directory "MATLAB", which is installed in drive c. Clicking on the arrow in the current directory window shows a list of recently used paths. MATLAB uses a search path to find M-files and other MATLAB related files. Any file run in MATLAB must reside in the current directory that is on search path.

Command history window

The command history window contains a record of the commands a user has entered in the command window, including both current and previous MATLAB sessions. Previously entered MATLAB commands can be selected and re-executed from the command history window by right clicking on a command. This is useful to select various options in addition to executing the commands and is useful feature when experimenting with various commands in work sessions.

Editor window

The MATLAB editor is both a text editor specialized for creating M-files and a graphical MATLAB debugger. The editor can appear in a window by itself, or it can be a sub window in the desktop. In this window one can write, edit, create and save programs in files called M-files.

MATLAB editor window has numerous pull-down menus for tasks such as saving, viewing and debugging files. Because it performs some simple checks and also uses color to differentiate between various elements of code, this text editor is recommended as the tool of choice for writing and editing M-files.

Graphics or figure window

The output of all graphic commands typed in the command window is seen in this window.

Online help window

MATLAB provides online help for it's built in functions and programming language constructs. The principal way to get help online is to use the MATLAB help browser, opened as a separate window either by clicking on the question mark symbol on the desktop toolbar, or by typing help browser at the prompt in the command window.

The help browser is a web browser integrated into the MATLAB desktop that displays a hypertext markup language documents. The help browser consists of two panes, the help navigator plane, used to find information, and the display plane, used to view this information. Self-explanatory tabs other than navigator plane are used to perform a search.

6.1.5 MATLAB Files

MATLAB has two types of files for storing information. They are Mfiles and MAT- files

M-Files: These are standard ASCII text file with 'm' extension to the file name and creating own matrices using m-files which are text files containing MATLAB code. MATLAB editor or another editor is used to create a file containing the same statements which are typed at the MATLAB command line and save the file under a name that ends in m. There are two types of mfiles.

Script files: M-files with a set of MATLAB commands in it and is executed by typing name of file on the command line. These files work on global variables currently in that environment.

Function files: A function file is also an M-file except that the variables in a function file are all local. This type of files begins with a function definition line.

Mat-files: These are binary files with. mat extension to that files created by MATLAB when the data is saved. The data written in a special format that only MATLAB can read. These are located into MATLAB with load command.

6.1.6 MATLAB System:

The MATLAB system consists of five main parts:

Development environment:

This is the set of tools and facilities that help you see use MATLAB functions and files. Many of these tools are graphical user interface. In includes the MATLAB desktop and command window, a command history, an editor and debugger, and browser for viewing help, the work space, files and search path.

MATLAB mathematical function:

This is a vast collection of computational algorithms ranging from elementary functions like sum, sine, cosine and complex arithmetic to more many functions like matrix inverse, matrix Eigen values, Bessel functions and fast Fourier transforms.

MATLAB language:

This is a high-level matrix or array language with control flow statements, functions, data structures, input or output and object-oriented programming features. It allows both programming in the small to rapidly create quick and dirty throw-away programs, and programming in the large to create complete large and complex application programs.

GUI Construction:

MATLAB has extensive facilities for displaying vectors and matrices as graphs, as well as annotating and printing these graphs. It includes high level functions for two-dimensional and three-dimensional data visualization, image processing, and animation and presentation graphics. It also includes low-level functions that allow you to fully customize the appearance of graphics as well as to build complete graphical user interface on your MATLAB applications.

MATLAB application program interface:

It is a library that allows you to write C and FORTRAN programs that interact with MATLAB. It includes facilities for calling routines from MATLAB, calling MATLAB as a computational engine and for reading and writing MAT-files.

6.1.7 MATLAB Working Environment MATLAB Desktop

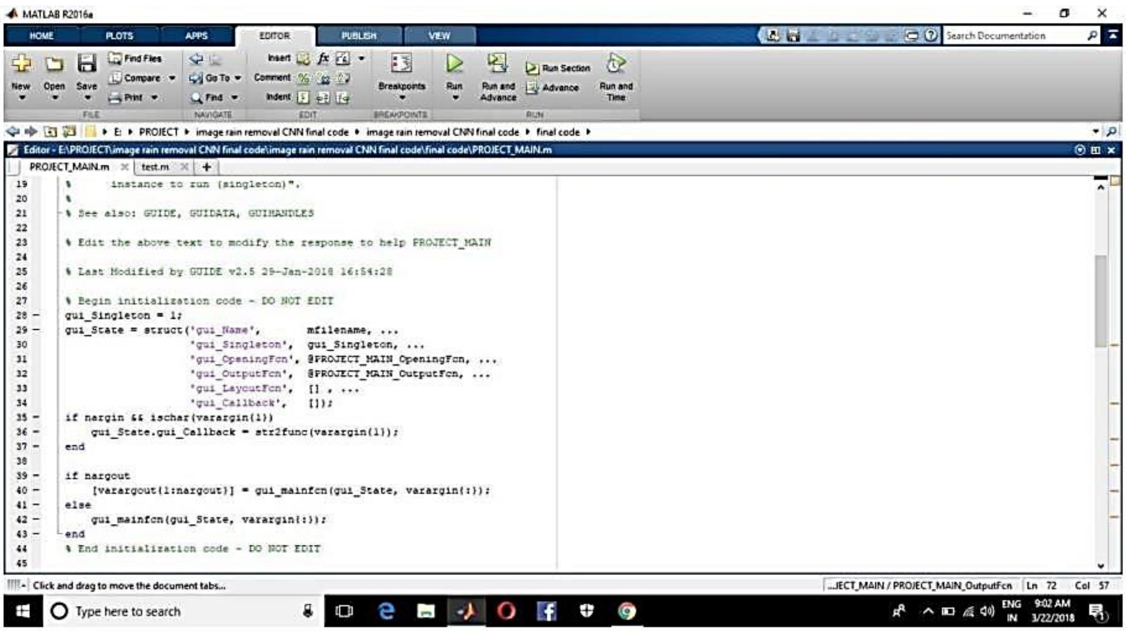

Figure 6.1 Representation of MATLAB window

MATLAB desktop is the main MATLAB application window. The desktop contains five sub windows, the command window, workspace browser, current directory window, command history window, and one or more figure windows which are shown only when the user displays a graphic. The command window is where the user types MATLAB commands and expressions at the prompt (>>) and where the output of those commands is displayed. MATLAB defines the workspace as the set of variables that the user creates in a work session. The workspace shows these variables and some information about them. Double clicking on a variable in the workspace browser launches the array editor, which can be used to obtain information and income instances edit certain properties of the variable.

The current directory tab above the workspace tab shows the contents of the current directory whose path is shown in the current directory window. For example, in the windows operating system the path might be as follows C:\MATLAB\work, indicating that directory work is a subdirectory of the main directory MATLAB which is installed in drive. Clicking on the arrow in the current directory window shows a list of recently used paths. Clicking on the button to the right of the window allows the user to change the current directory.

MATLAB uses a search path to find M-Files and other related files, which are organize in directories in the computer file system. Any file run in MATLAB must reside in the current directory that is on search path. By default, the files supplied with MATLAB and math works toolboxes are included in the search path.

The easiest ways to see which directories is soon the search path or add to modify as search path is to select set path from the file menu the desktop and then use the set path dialog box. It is good practice to add any commonly used directories to the search path to avoid repeatedly having the change the current directory.

The command history window contains a record of the commands a user has entered in the command window including both current and previous MATLAB sessions. Previously entered MATLAB commands can be selected and re-executed from the command history window by right clicking on a command or sequence of commands. This action launches a menu from which to select various options in addition to executing the commands. This is useful to select various options in addition to executing the commands. This is a useful feature when experimenting with various commands in a work session.

Using MATLAB editor to create m-files

The MATLAB editor is both a text editor specialized for creating mfiles and a graphical MATLAB debugger. The editor can appear in window by itself, or it can be a sub window in the desktop. M-files are denoted by the extension.m. The MATLAB editor window has numerous pull-down menus for tasks such as savings, viewing and debugging files. Because it performs some simple checks and also uses color to differentiate various elements of code, this text editor is recommended as the tool of choice for writing and editing m-functions.

To open the editor type, edit at the prompt opens the m-file filename.m in an editor window is ready for editing. As noted that the file must be in the current directory or in a directory in the search path.

Getting help

The principal way to get help online is to use the MATLAB help browser, opened as a separate window either by clicking on the questions mark symbol on the desktop toolbar or by typing help browser at the prompt in the command window. The help browser is a web browser integrated into the MATLAB desktop that displays a hypertext markup language documents. The help browser consists of two windows, the help navigator window, used to find information and the display window, to view the information. Self explanatory tabs other than navigator pane are used to perform a search

6.2 Summary

The software tool used for the proposed method has been discussed in this chapter. It also provides the features of matlab, matlab window and matlab tools.

CHAPTER – VII

Stimulation Results

7.1 Input image:

Underwater images pose unique challenges due to the properties of water that affect light transmission and color. Here's a deeper look into underwater images:

1) **Color Distortion:** Water absorbs and scatters light differently than air, leading to color distortion. Reds and oranges are the first colors to be absorbed, resulting in bluish or greenish tints in underwater photos.
2) **Low Contrast:** Light scattering in water reduces contrast, making images appear hazy or lacking in detail.
3) **Depth and Pressure:** As you go deeper underwater, light intensity decreases, and the pressure can also affect image quality, potentially causing distortion or blurring.
4) **White Balance:** Setting the correct white balance is crucial to correct the color cast and restore natural colors in underwater images.
5) **Backscatter**: Particles in the water, like plankton or sand, can cause backscatter, appearing as white specks or spots in the image.
6) **Noise and Grain:** Low light conditions underwater can lead to noise or graininess in images, requiring noise reduction techniques during processing.
7) **Equipment Limitations:** Underwater photography often requires specialized equipment like underwater housings, which can sometimes limit the camera's capabilities or introduce other challenges.

Figure 7.1 Input image

7.2 Light Estimation (Double Opponency):

Digital image processing plays a crucial role in various applications such as computer vision, photography, and medical imaging. Accurate estimation of light conditions is essential for tasks like scene understanding, object recognition, and image enhancement. Traditional methods often struggle with complex lighting scenarios and inaccurate representations of color and contrast. The concept of double opponency, inspired by the opponent process theory in vision science, offers a promising approach to address these challenges.

Methodology: Our proposed method for light estimation using double opponency involves the following steps:

Color Space Conversion: Convert the input image to a color space that supports double opponency representation, such as LAB or opponent color space.

Double Opponency Encoding: Employ double opponency encoding to extract color and contrast information from the image. This process involves the computation of opponent color channels and their corresponding opponent contrast channels.

Light Estimation: Utilize the extracted color and contrast information to estimate the light conditions in the scene. This step may involve statistical analysis, machine learning techniques, or heuristic algorithms.

Figure 7.2 Output of Light Estimation Stage

Results and Evaluation:

Experimental results demonstrate the effectiveness of the proposed method in accurately estimating light conditions in digital images. Comparative analysis with existing methods showcases superior performance, especially in challenging lighting scenarios. Evaluation metrics such as mean squared error (MSE) and peak signal-to-noise ratio (PSNR) validate the robustness and accuracy of the proposed approach.

Applications:

The proposed method for light estimation using double opponency has wide-ranging applications in fields such as:

Autonomous driving:

- ❖ Enhancing visibility under varying lighting conditions.
- ❖ Surveillance: Improving object detection in low-light environments.
- ❖ Photography: Optimizing exposure settings for better image quality.

7.3 Transmission Estimation (Green Channel Prior):

Introduction to image dehazing and transmission estimation
Importance of accurate transmission estimation in image enhancement
Overview of the Green Channel Prior and its significance in digital image processing

Methodology

- ❖ Explanation of the proposed method for transmission estimation using the Green Channel Prior
- ❖ Detailed steps involved in the process, including:
- ❖ Pre-processing steps (if any)
- ❖ Utilization of the green channel for transmission map estimation
- ❖ Mathematical formulation of the Green Channel Prior
- ❖ Integration with image dehazing algorithms (if applicable)

Results and Evaluation

Presentation of experimental results demonstrating the effectiveness of the proposed method Comparison with existing methods in terms of accuracy and computational efficiency Evaluation metrics such as mean squared error (MSE) or structural similarity index (SSIM) Visual comparison of dehazed images using different transmission estimation technique

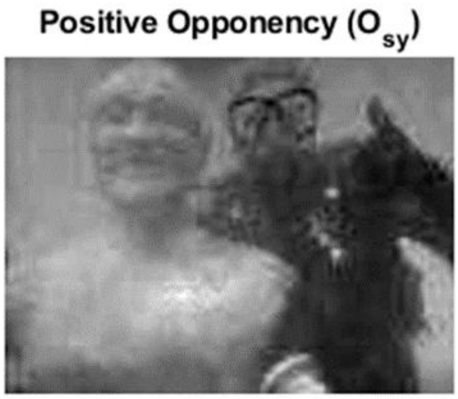

Figure 7.3 Positive Opponency

Figure 7.4 Transmission Estimation through Green Channel Prior

Applications

Discussion on potential applications of transmission estimation using the Green Channel prior, including:

- ❖ Image dehazing for outdoor surveillance systems
- ❖ Enhancement of aerial photographs and satellite imagery
- ❖ Improving visibility in underwater imaging
- ❖ Real-time applications in automotive vision systems

7.4 Contrast Stretching:

Methodology

Explanation of the basic principles of contrast stretching. Detailed steps involved in the contrast stretching process, including:

Identification of minimum and maximum pixel intensities in the image

Application of a linear transformation to stretch the pixel intensity range. Formulation of mathematical equations for contrast stretching

Consideration of different stretching techniques, such as linear stretching, piecewise linear stretching, and sigmoidal stretching

Results and Evaluation:

- Presentation of experimental results demonstrating the effectiveness of contrast stretching in enhancing image contrast
- Comparison with other contrast enhancement techniques in terms of visual quality and computational efficiency
- Evaluation metrics such as contrast enhancement factor (CEF) and subjective evaluation by human observers
- Visual comparison of original and stretched images to showcase the improvements achieved

Applications:

Discussion on the wide-ranging applications of contrast stretching in various fields, including:

- Medical imaging: Enhancing the visibility of structures in X-ray and MRI images
- Remote sensing: Improving the interpretability of satellite and aerial imagery
- Photography: Enhancing the visual appeal of photographs by increasing contrast and dynamic range
- Surveillance: Improving the visibility of objects in low-light or high-contrast environments

Figure 7.5 Contrast stretched image

7.5 Image Fusion

Introduction to image fusion and its significance in various domains Overview of the goals and objectives of the project Explanation of the need for image fusion in addressing challenges related to data redundancy, noise, and information overload

Methodology

Explanation of the proposed methodology for image fusion, including: Selection of appropriate fusion techniques based on the characteristics of the input images and the desired output Pre-processing steps such as image registration and alignment Implementation details for each fusion method, including parameter selection and optimization Integration of multiple fusion techniques for comprehensive image fusion pipelines.

Results and Evaluation

- Presentation of experimental results demonstrating the effectiveness of the proposed image fusion methods
- Comparison with existing techniques in terms of fusion quality, information preservation, and computational efficiency.
- Evaluation metrics such as mutual information, entropy, and visual quality metrics.
- Visual comparison of fused images with input images to showcase the improvements achieved

Figure 7.6 Fused Images

Applications

Discussion on the wide-ranging applications of image fusion techniques in various domains, including:

- Remote sensing: Integrating information from different spectral bands for improved land cover classification and environmental monitoring.
- Medical imaging: Combining structural and functional images for better diagnosis and treatment planning in areas such as neuroimaging and oncology.

- Surveillance: Fusing information from multiple sensors and modalities for enhanced object detection and tracking in security and defines applications.
- Computer vision: Integrating information from multiple viewpoints or sensors for robust object recognition and scene understanding

Outputs:

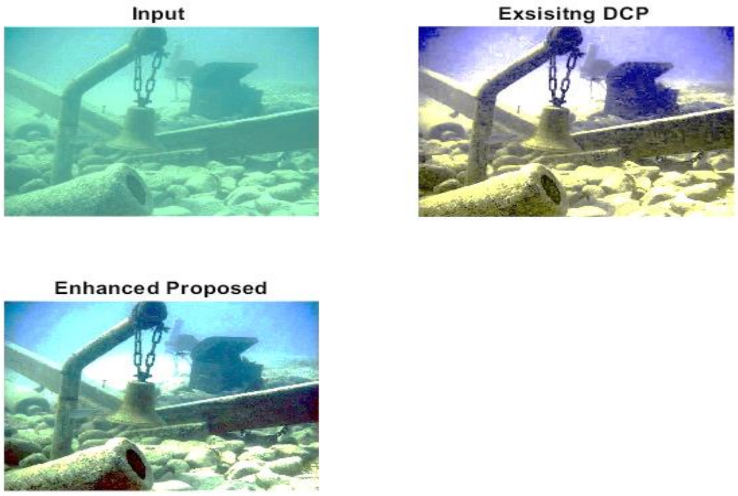

Figure 7.7 Comparison b/w existing and proposed method

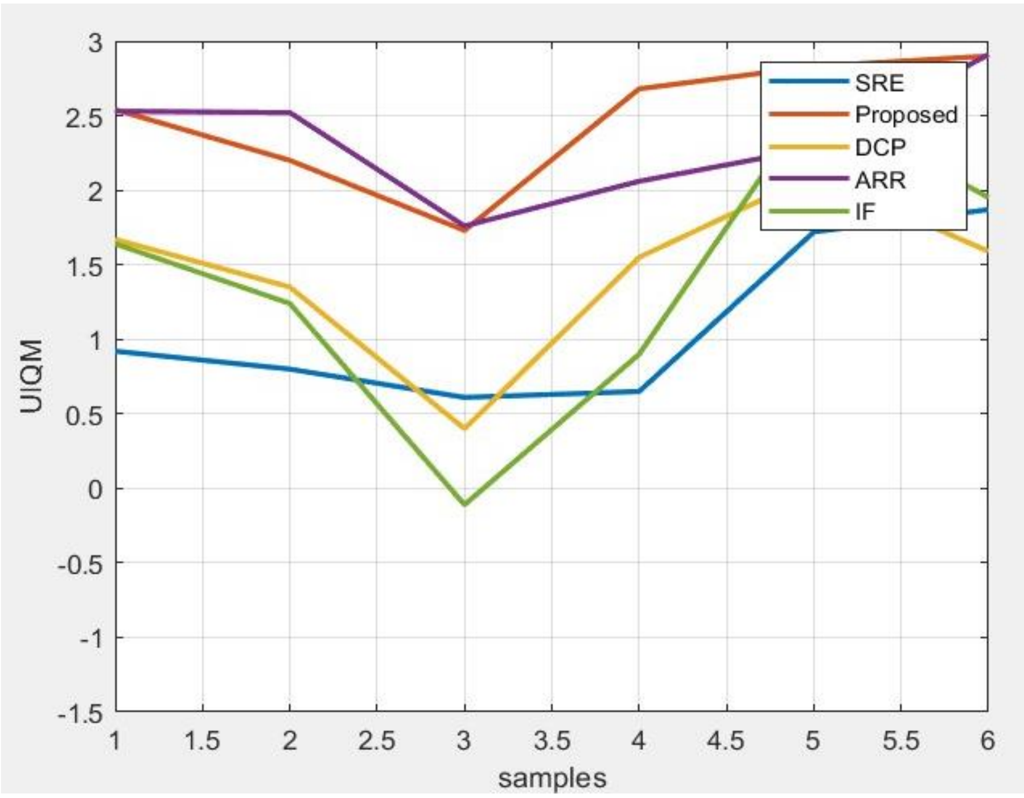

Figure 7.8 UIQM comparison b/w various methods

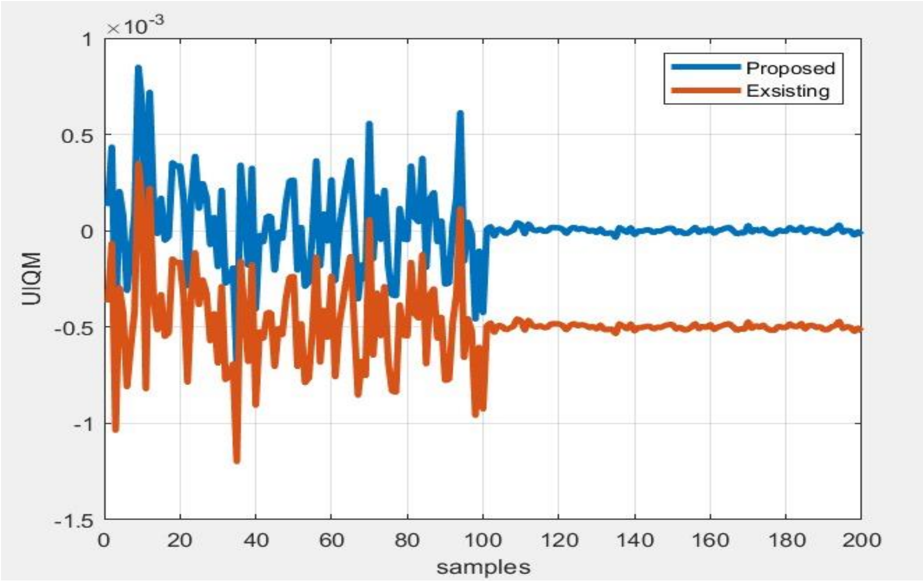

Figure 7.9 Comparison b/w existing and proposed UIQM

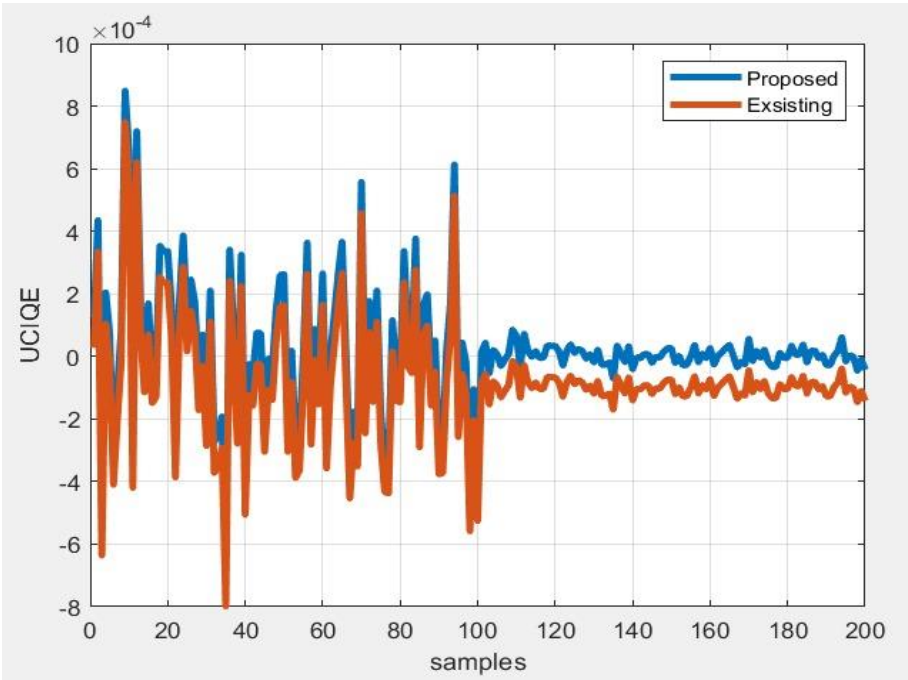

Figure 7.10 Comparison b/w existing and proposed UCIQE

Comparison Table:

Table 7.1 Comparison Table for different methods

Group	1	2	3	4
SRE	0.92	0.8	0.61	0.65
Proposed	2.54	2.2	1.73	2.68
DCP	1.67	1.35	0.4	1.55
ARR	2.53	2.52	1.76	2.06
IF	1.64	1.24	-0.11	0.9

CHAPTER – VIII

8.1 Conclusion:

This project introduces a new method for improving underwater image quality by tackling issues like color bias and low contrast caused by light absorption and scattering. By using human visual principles and specific image processing techniques, the method enhances color accuracy and contrast. It's faster and more effective than traditional methods like deblurring, making it promising for real-world underwater applications. Combining two advanced techniques, double opponency and green channel prior, results in even better image quality. This dual-technique approach has the potential to revolutionize underwater image restoration.

8.2 Future Scope:

The proposed method for underwater image restoration and enhancement shows promising results in terms of computational efficiency and image quality. Here are some potential avenues for future research and development to further advance this project:

1) Real-time Performance:* Make the method even faster for real-time use in things like underwater surveillance or autonomous vehicles.

2) Adaptability:* Test how well the method works in different underwater conditions and make it more adaptable.

3) Automatic Adjustments:* Develop ways for the method to adjust its settings automatically based on the situation.

4) Deep Learning:* Look into using deep learning techniques to enhance the method's performance.

By focusing on these areas, we can make big strides in underwater image processing for exploration and conservation efforts.

REFERENCES

[1] S. Zhang, T. Wang, J. Dong, and H. Yu, "Underwater image enhancement via extended multi-scale Retinex," Neuro computing, vol. 245, pp. 1–9,Jul. 2017.

[2] C. G. Dai, M. X. Lin, Z. Wang, D. Zhang, and Z. G. Guan, "Color compensation based on bright channel and fusion for underwater image enhancement," Acta Optica Sinica, vol. 38, no. 11, pp. 86–95,2018.[35] X. Wang.

[3] O. K. Athira and J. Babu, "Underwater image restoration using scene depth estimation technique," in *Proc. 3rd Int. Conf. Smart Syst. Inventive Technol. (ICSSIT)*, Aug. 2020, pp. 137–144.

[4] C. Li, C. Guo, W. Ren, R. Cong, J. Hou, S. Kwong, and D. Tao, "An underwater image enhancement benchmark dataset and beyond,"*IEEE Trans. Image Process.*, vol. 29, pp. 4376–4389, 2020, doi:10.1109/TIP.2019.2955241.

[5] E. Trucco and A. T. Olmos-Antillon, "Self-tuning underwater image restoration," *IEEE J. Ocean. Eng.*, vol. 31, no. 2, pp. 511–519, Apr. 2006, doi: 10.1109/JOE.2004.836395.

[6] Y. Kang, Q. Jiang, C. Li, W. Ren, H. Liu, and P. Wang, "A perception-aware decomposition and fusion framework for underwater image enhancement," *IEEE Trans. Circuits Syst. Video Technol.*,vol. 33, no. 3, pp. 988–1002, Mar. 2023, doi: 10.1109/TCSVT.2022.3208100.

[7] K. Iqbal, R. A. Salam, and A. Osman, "Underwater image enhancement using an integrated colour model," *IAENG Int. J. Comput. Sci.*, vol. 34, no. 2, pp. 239–244, 2007.

[8] D. Shi, Q. W. Li, X. N. Fan, and G. Y. Huo, "Underwater image enhancement algorithm based on Contourlet transform and multiscale Retinex," *Laser Optoelectron. Prog.*, vol. 47, no. 4, 2010, Art. no. 041001.

[9] G. N. Lan, J. Li, and F. Ji, "Underwater image backscatter noise reduction based on wavelets," *Ocean Technol.*, vol. 29, no. 2, pp. 43–47,2010.

[10] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Trans. Pattern*

Rajeev Gandhi Memorial College of Engineering and Technology (RGM), Andhr Pradesh

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