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Submission date: 21-May-2026 09:23AM (UTC+0530)

Submission ID: 2966111857

File name: Mtech_Thesis_formatting__Copy__Copy__5.pdf (5.23M)

Word count: 13925

Character count: 77835

**A SYSTEMATIC STUDY AND
COMPARATIVE ANALYSIS OF
UNDERWATER IMAGE ENHANCEMENT
TECHNIQUES WITH EMPHASIS ON
FUZZY HISTOGRAM EQUALIZATION**

A THESIS
SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF

MASTERS OF TECHNOLOGY
IN
SOFTWARE ENGINEERING

Submitted by
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ACKNOWLEDGEMENT

I would like to express my sincere gratitude to **Dr. Sonika Dahiya**, Assistant Professor, Department of Software Engineering, Delhi Technological University, for her invaluable guidance, support, and encouragement throughout the preparation of this report. Her insights and expertise were instrumental in shaping the direction of my research and explaining all the tasks to be accomplished, emphasising the importance of this work as well as its relevance to real-world applications.

I would also like to thank all the teachers and students of the Department of Software Engineering, Delhi Technological University, for providing the necessary resources, continuous support, and valuable suggestions that facilitated the completion of this research. Lastly, I would like to thank all my family and friends for providing continuous support and motivation during the process of this study.

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I Priyanshu Jain, Roll No. 2K24/SWE/01 hereby certify that the work which is being presented in the thesis entitled "A Systematic Study and Comparative Analysis of Underwater Image Enhancement Techniques with Emphasis on Fuzzy Histogram Equalization" in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from January 2026 to May 2026 under the supervision of Dr. Sonika Dahiya.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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A Systematic Study and Comparative Analysis of Underwater Image Enhancement Techniques with Emphasis on Fuzzy Histogram Equalization

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ABSTRACT

A critical issue for marine applications is underwater image enhancement. Light absorption and scattering at different wavelengths degrade underwater images producing contrast-loss and color distortion and structural degradation. The Fuzzy Histogram Equalization (FHE) has been considered as a potentially fruitful family of techniques to deal with intensity uncertainties using membership functions. The major gap within this area is the absence of a systematic and comparative study on different FHE techniques as well as the lack of clear evidence of what factors actually affects the performance of the FHE algorithms.

To fulfill the above purpose, this thesis is two-fold. First, the author conducts a systematic review of twelve FHE-related techniques published between 2017 and 2024, grouping the methods into bi-histogram, weighted, contextual, adaptive, intuitionistic, and type-2 fuzzy approaches. The review reveals that a fixed membership parameter is a consistent central limitation across all the analyzed techniques. Second, based on controlled experiments involving fourteen techniques across four standard datasets, the study concludes that adaptive ability and coupled color correction, not complexity of membership function, determine the performance of FHE. FIMHE automatically sets the clip limit based on the fuzziness of each input image, and thus consistently achieves good structural quality. FCCE achieves higher perceptual quality as it is grounded in context-aware membership functions; however, the loss of structural quality is notably large. In addition, intuitionistic and type-2 fuzzy methods offer no notable structural benefit over standard HE.

LIST OF PUBLICATIONS

1. **Priyanshu Jain, Dr. Sonika Dahiya, and Priyanka Arora** (2026). "A Review of Underwater Image Enhancement Techniques with Emphasis on Fuzzy Histogram Equalization." [*Scopus Indexed*] [Accepted - ICICC 2026, Springer LNNS Series]
2. **Priyanshu Jain and Dr. Sonika Dahiya** (2026). "A Comparative Analysis of Underwater Image Enhancement Techniques: Classical, Fuzzy Logic-Based, Physics-Based, and Fusion Approaches." [*Scopus Indexed*] [Accepted - ICDAM 2026, Springer LNNS Series]

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LIST OF ABBREVIATIONS

AUV	Autonomous Underwater Vehicle
BHEFPL	Bi-Histogram Equalization with Fuzzy Plateau Limit
CLAHE	Contrast Limited Adaptive Histogram Equalization
CLFAHE	Contrast Limited Fuzzy Adaptive Histogram Equalization
CDF	Cumulative Distribution Function
EUVP	Enhancing Underwater Visual Perception
FCCE	Fuzzy-Contextual Contrast Enhancement
FCW_HE	Fuzzy Colour Histogram Equalization with Weighted Distribution
FD_CHE	Fuzzy Dissimilarity Colour Histogram Equalization
FHE	Fuzzy Histogram Equalization
FHE_ACC	Fuzzy Histogram Equalization with Adaptive Colour Correction
FIMHE	Fuzzy Intensity Measure Adaptive Clipping Histogram Equalization
HE	Histogram Equalization
HSV	Hue, Saturation, Value
IFG_ACC	Intuitionistic Fuzzy Generator with Adaptive Colour Correction
IFHE	Intuitionistic Fuzzy Histogram Equalization
IFHE_JB	Intuitionistic Fuzzy Histogram Equalization (Jebadass & Balasubramaniam)
IFLAHF	Improved Fuzzy Logic Adaptive Histogram Framework
NTU	Nephelometric Turbidity Unit
PSNR	Peak Signal-to-Noise Ratio
SSIM	Structural Similarity Index
T2FHE	Interval Type-2 Fuzzy Histogram Equalization
UIEB	Underwater Image Enhancement Benchmark
UIConM	Underwater Image Contrast Measure
UICM	Underwater Image Colourfulness Measure
UIQM	Underwater Image Quality Measure
UISM	Underwater Image Sharpness Measure

CHAPTER 1

INTRODUCTION

The practice of underwater imaging plays a fundamental role in a variety of scientific, industrial, and navigational applications, ranging from the inspection of underwater environments and navigation of unmanned vehicles to underwater archaeology and the exploration of underwater features [1]. It is crucial that underwater scenes are imaged to provide clear, color-rich, and detail-rich representations of submerged subjects. Unfortunately, due to the nature of light propagation underwater, these characteristics pose a major problem when capturing clear images, compared to imaging in air.

In addition to the wavelength-dependent absorption, light scattering is an issue when light is travelling through water. Red wavelengths are almost entirely absorbed within just a few meters of water depth, leaving only the blue and green wavelengths, resulting in underwater images taking on a predominantly bluish-green appearance. Another consequence of the presence of suspended particles is that image contrast is attenuated by scattering which, causes a "haze", making fine detail invisible. Over these parameters add to the variables, which are turbidity, depth, and bad/non-uniform illumination; and out-of-the-box underwater images become unusable in numerous applications [2].

There are a lot of enhancement methods, which are designed to solve the problem. Classical methods as HE and CLAHE have been widely used. These methods improve contrast but introduce drawbacks such as noise, artefacts, and color distortion [3]. Fuzzy logic-based enhancement methods and their derivatives have shown promising results by using membership functions to handle uncertainty in pixel intensity distributions [4]. Nevertheless, a systematic comparative analysis of FHE-type methods under identical conditions is absent, and the factors that determine FHE performance have not been clearly established.

1.1 Problem Statement

Underwater image enhancement is still an open and challenging problem. In general, the key obstacles to underwater image enhancement are wavelength-dependent light absorption, scattering, and non-uniform illumination, which result in low contrast, blue-green color distortion, and loss of structural detail. Furthermore, traditional methods tend to over-enhance the image and amplify noise; fuzzy logic-based methods have fixed membership function parameters and therefore lack the adaptability to handle various underwater environments [3, 5].

Another problem is that all of the FHE methods have not been simultaneously compared on a common data set using common performance criteria in a controlled comparison study. Most methods are evaluated individually or only on a selection of methods belonging to a specific category, which makes it hard to conclude which one is best. Lastly, what affects FHE performances has never been systematically investigated empirically; factors such as the used membership function, adaptivity of the method, complementarity of colour correction, etc., are still not clear.

This dissertation addresses these gaps through two contributions. The first is a systematic review of FHE methods published in the scientific literature from 2017 to 2024, and the second is a controlled experiment evaluating fourteen methods spanning classical and fuzzy logic-based categories.

1.2 Research Objectives

1. To analyze and categorize exemplary FHE-based methods appearing in the literature from 2017 to 2024, outlining their fundamental categories, strengths and limitations, as well as the main limitation of a constant membership function.
2. To apply and assess fourteen methods across classical and fuzzy logic-based categories, including HE, CLAHE, and twelve FHE-based methods, on two randomly selected images from each of the sets in the UIEB dataset and three sets in the EUVP dataset, using PSNR, SSIM, and UIQM.
3. To study the structural and perceptual trade-offs among all fourteen methods and empirically identify the main factors determining the performance of FHE-based methods, whether it be the complexity of the membership function, spatio-adaptivity, or complementary color correction.
4. To provide, based on empirical evidence, an objective recommendation for selecting a method for underwater image enhancement, as well as to suggest future directions for research in the area of adaptive fuzzy histogram equalization.

1.3 Overview of the Study

Two complementary parts are developed, in this dissertation, that complement each other directly based on the outcome of the one before, as seen in Figure 1.1.

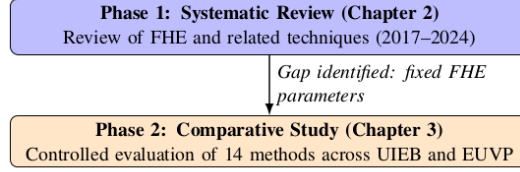


Figure 1.1: Overview of the Two-Phase Research Design

Phase 1: Systematic Review (Chapter 2): This chapter provides an in-depth and systematic review of underwater image enhancement techniques published from 2017 to 2024. It focuses particularly on FHE methods and their extensions. Twelve FHE techniques are identified, summarized, and grouped into three categories. Fixed membership parameters are identified as a common limitation across the FHE techniques.

Phase 2: Comparative Study (Chapter 3): The second stage presents a controlled comparative empirical analysis of all fourteen classical and fuzzy logic-based methods. All methods are tested on two randomly sampled images from the UIEB dataset and from each of the three subsets of the EUVP dataset, using the PSNR, SSIM, and UIQM metrics. In-depth examination of the twelve FHE methods showed that adaptability and correction of colors are the primary factors of best enhancement.

The structure of the rest of this dissertation is as follows. Chapter 2 gives a thorough review of the FHE-based approaches and variations. Chapter 3 covers the experimental set-up, outcomes and analysis of the FHE-based methods. Chapter 4 contains the conclusion, future scope and social impact.

CHAPTER 2

REVIEW OF UNDERWATER IMAGE ENHANCEMENT TECHNIQUES WITH EMPHASIS ON FUZZY HISTOGRAM EQUALIZATION

The present chapter offers a survey of the underwater image enhancement algorithms published from 2017 to 2024, especially the FHE methods and their extensions. Methods are grouped into three broad categories of techniques, namely, conventional histogram based methods, fuzzy logic based methods and hybrid/multi-scale methods. This chapter is structured to include search methodology, public domain datasets for the subject area, a comparison of performances of discussed methods, FHE application in underwater image enhancement and existing major open issues.

2.1 Introduction to Fuzzy Histogram Equalization

Underwater imaging plays a vital role in exploration, observation and navigation. Light attenuates and scatters through water in different wavelengths, leading to loss of structure and image contrast, a dominant blue-green coloration of images [2]. Such degradation in underwater images is inappropriate for tasks such as object detection, marine species recognition and AUV navigation [1].

Despite its computational efficiency, Histogram Equalization (HE) remains widely used for underwater image enhancement. However, classical HE tends to produce over-enhanced results [3]. To overcome these, some methods like CLAHE [6], fuzzy logic-based methods [4] have been suggested. Fuzzy Histogram Equalization, uses membership functions, dealing with uncertainty in pixel intensity distributions, producing controlled results [7].

Even though all the above works overcome limitations, there are common issues with all categories of methods: unadaptive parameters to change environment in underwater condition [3], noise amplification [5], lack of real time ability [8] and trade off problem of color restoration versus contrast enhancement. In turbid water, problems of spectral restoration would be more severe in wavelengths larger than 550 nm, as high NTU and chlorophyll contamination distort spectral restoration.

To the best of our knowledge, it is the first survey about FHE and its

variations applied to underwater image enhancement within the years of 2017-2024. There are three key findings from this survey. One is the “static parameter paradox”: current FHE approaches are using static, non-adaptive parameters that do not adapt to turbidity and illumination variation of underwater environments. Another is the principled fuzzy handling of intensity uncertainty by membership functions, but it is not well utilized in current systems as all parameters are static. Finally, there are two inherent limitations which are the trade-off between complexity and quality for AUV operations, and colour correction in the region over 550 nm.

2.2 Search Methodology

This systematic review followed a step-by-step process composed of the following four phases: Planning, Literature Selection, Data Extraction and Synthesis, and Reporting. The entire workflow of the systematic review is represented in Figure 2.1.

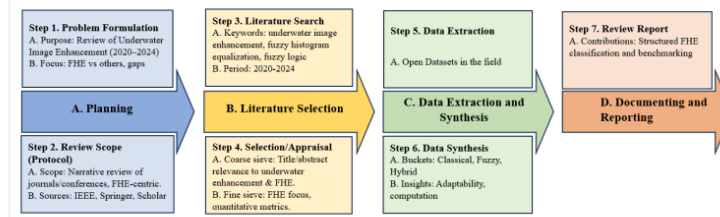


Figure 2.1: Workflow of the Review Methodology

2.2.1 Search Process

A literature search for underwater image enhancement and FHE was performed on Google Scholar, IEEE Xplore, ScienceDirect, and Springer Online Library. An example of the search strings used is shown in Figure 2.2.

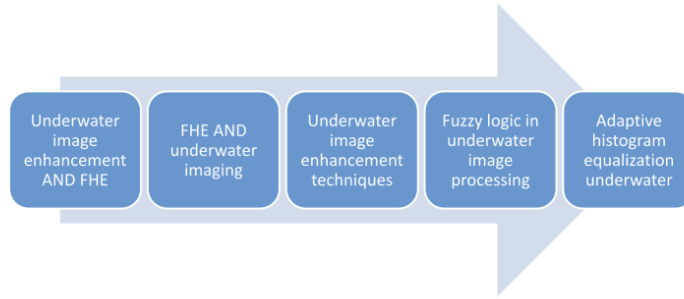


Figure 2.2: Search Strings Used for Literature Retrieval on Underwater Image Enhancement

Some of the keywords are as following: “*underwater image enhancement and fuzzy histogram equalization*”, “*FHE and underwater imaging*”, “*underwater image enhancement techniques*”, “*fuzzy logic in underwater image processing*”, and “*adaptive histogram equalization for underwater images*”. Search result were only limited to peer-reviewed journal articles and conference papers from 2017 to 2024.

2.2.2 Selection Criteria

A two stage screening procedure was used. The first step (coarse sieve) involved re-viewing titles and abstracts to identify studies related to underwater image enhancement and FHE. The second step (fine sieve) involved screening the entire paper to confirm whether FHE or some other fuzzy logic technique was used, whether the study included some form of quantitative metric, and whether it had been published in a peer-reviewed journal. Papers that only relied on deep learning without employing histograms or fuzzy components were excluded from consideration.

2.3 Underwater Image Enhancement Techniques

This section categorises the reviewed techniques into three major groups: classical enhancement techniques, fuzzy logic-based techniques, and hybrid and multi-scale techniques. Figure 2.3 illustrates this classification.

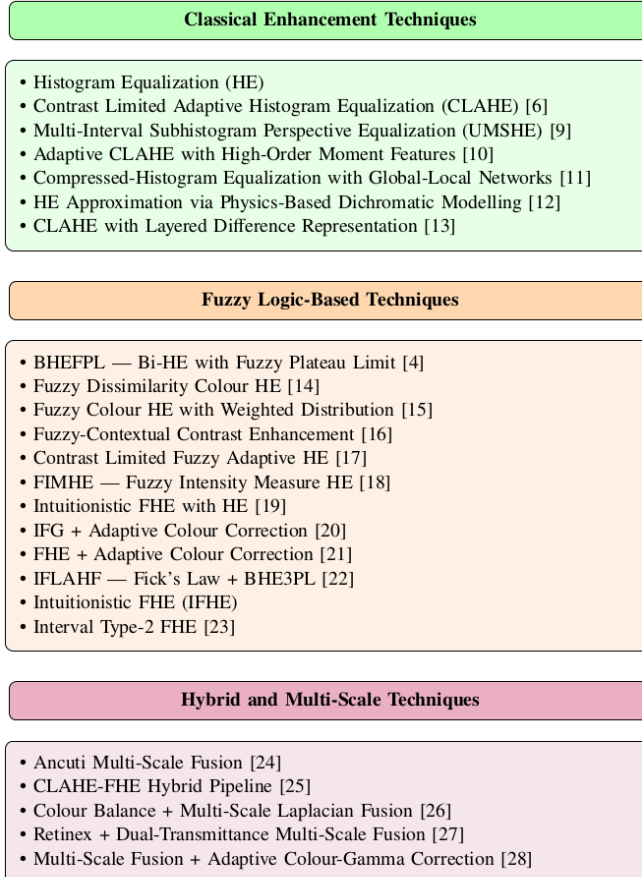


Figure 2.3: Categorization of Underwater Image Enhancement Techniques (2017–2024)

2.3.1 Classical Enhancement Techniques

Classical histogram-based methods improve global or local contrast without explicit physical modelling of the underwater degradation process. Histogram Equalization (HE) redistributes pixel intensities across the full dynamic range at negligible computational cost but produces over-enhanced results and amplifies noise in non-uniformly illuminated underwater scenes [3, 5].

CLAHE [6] addresses this by applying localised histogram equalisation within image tiles and limiting contrast amplification through a clip limit. Grandhi and Pilli [29] developed a combination of CLAHE with DSIHE and White Balance correction in order to obtain good colour correction. Ulutas and Ustubioglu [13] modified CLAHE by a layered difference representation. This enhances edge detail in local regions while suppressing halo effects more effectively than original CLAHE.

Zhou et al. [9] proposed UMSHE, a multi-interval subhistogram perspective equalization method that divides the histogram into adaptive sub-intervals for local contrast enhancement while controlling brightness deviation. Chen and Liang also introduced a CLAHE variation [10] in which the clip limit is adaptively estimated based on higher-order moments in every block of image.

A global-local network with compression histogram equalization which handles both global color cast and local contrast simultaneously was designed by Fu and Cao [11]. An HE approximation method based on physics-based dichromatic modelling was presented by Peng et al. [12], which balances between contrast enhancement and physically motivated color correction for natural-looking result.

However, despite their efficiency in computation, these classical methods do not consider the non-linear depth related degradation that prevails in underwater environment, and do not model color except through shifting of the intensity distribution [7].

2.3.2 Fuzzy Logic-Based Techniques

The FHE model represents pixel intensity using membership functions, allowing it to deal with the uncertainty of the pixel intensity distribution [7]. Unlike conventional methods that assign crisp labels to pixels, fuzzy methods assign degrees of membership that better capture the continuous and uncertain nature of underwater intensity degradation. This subsection reviews twelve FHE-related approaches published between 2017 and 2024, all of which are evaluated experimentally in Chapter 3.

Bi-Histogram and Plateau-Based FHE: Fazal and Khan [4] suggested Bi-Histogram Equalization with Fuzzy Plateau Limit (BHEFPL) where the image histogram is split based on image mean and then each sub-histogram is applied with a fuzzy plateau limit to prevent over-enhancement beyond a certain limit, with 21.21 PSNR and 0.865 SSIM for custom data. Liu et al. [22] extended this to the Bi-histogram optimized framework of IFLAHF where 3 plateau limits are used and are based on Fick's Law Algorithm for parameter determination (BHE3PL), which overcomes the fixed parameter aspect of earlier FHE methods.

Weighted and Dissimilarity-Based FHE: Veluchamy and Subramani [14] proposed fuzzy dissimilarity color histogram equalisation, that computes dissimilarity between gray level using fuzzy set theory, and includes color correction for simultaneous enhancement of both contrast and color cast. Mayathevar et al. [15] proposed fuzzy color histogram equalisation with weighted distribution, where the weight computed using local statistics of the image is used to equally reassign the histogram values, thus rendering more realistic tonal distribution than FHE with fixed weights.

Adaptive and Contextual FHE: Parihar et al. [16] suggest a fuzzy-contextual contrast enhancement method where contextual information about each pixel is used to determine its fuzzy membership, rather than just using the global average. This is intended to result in a spatially sensitive enhancement of the image. Magudeeswaran and Singh [17] describe a method of contrast limited fuzzy adaptive histogram equalization. They combine the concept of a fuzzy membership function with the CLAHE approach of a clip limit to prevent an image from becoming too severely enhanced while still allowing the adaptability of the fuzzy mapping of intensities. Zhu et al. [18] present a method they call Fuzzy Intensity Measure and Adaptive Clipping Histogram Equalization (FIMHE). This uses a fuzzy intensity measure in an attempt to define the local properties of an image, which is then used to adapt a clipping threshold for each block of the image. This method attempts to be a middle ground between a global FHE method and spatially adaptive enhancement.

Intuitionistic FHE: Intuitionistic Fuzzy set is an extension of type-1 Fuzzy Set, which assigns membership (μ), non-membership (ν), and hesitancy (π) values to each pixel and enables a more expressive modelling of uncertainty. Jebadass and Balasubramaniam [19] proposed an intuitionistic fuzzy set based algorithm for enhancement of low light color image which not only includes the membership and non membership values but also uses a boosting parameter to determine how hesitant is the intuitionistic fuzzy set. Rani et al. [20] used Intuitionistic Fuzzy Generator (IFG)

combined with adaptive color correction technique in order to enhance both color integrity and structural fidelity in underwater images.

FHE for Underwater Images Specifically: According to Suharyanto et al. [21], the method for underwater images that uses both fuzzy histogram equalization and adaptive color correction aims to enhance images from both sides by resolving intensity ambiguity and color cast issues common in underwater images simultaneously.

Advanced Fuzzy HE: The Intuitionistic Fuzzy Histogram Equalization (IFHE) process utilizes the score function, $s(x) = \mu(x) - \nu(x)$, from intuitionistic fuzzy sets, to develop the same idea as Basic FHE. This method yields a more diverse tonal distribution, as opposed to just single membership. The Interval Type-2 Fuzzy Histogram Equalization (Type-2 FHE) models uncertainty in the membership function itself using an interval $[\mu_{\text{lower}}, \mu_{\text{upper}}]$ computed from the mean and standard deviation of the V channel, making it theoretically more robust to intensity uncertainty caused by underwater scattering [23].

The persistent limitation across all reviewed fuzzy logic-based methods is the use of fixed or semi-fixed membership function parameters that cannot fully adapt to varying underwater conditions [3]. Table 2.1 summarises all twelve FHE-related techniques reviewed in this section.

Table 2.1: Summary of FHE-Related Techniques (2017–2024)

Method	Description	Advantage	Limitation
BHEFPL [4]	Bi-histogram equalization with fuzzy plateau limit; divides histogram at mean and applies fuzzy clipping to each sub-histogram	Prevents over-enhancement; preserves brightness better than standard HE	Fixed plateau limit; does not adapt to varying turbidity or scene content
Fuzzy Dissimilarity Colour HE [14]	Measures dissimilarity between pixel intensities using fuzzy set theory with colour correction	Addresses both contrast and colour cast simultaneously	Fixed dissimilarity threshold; limited adaptability to diverse scenes
Fuzzy Colour HE with Weighted Distribution [15]	Uses locally derived weights to adaptively redistribute histogram bins	More natural tonal distribution than equal-weight FHE	Weights computed globally; still lacks spatial adaptivity
Fuzzy-Contextual Contrast Enhancement [16]	Uses contextual pixel neighbourhood information to define spatially sensitive fuzzy membership values	Spatially aware enhancement; better local contrast control	Neighbourhood size fixed; context window not adaptive

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Table 2.1 – *Continued from previous page*

Method	Description	Advantage	Limitation
Contrast Limited Fuzzy Adaptive HE [17]	Combines fuzzy membership function with CLAHE-style clip limit for controlled enhancement	Prevents over-enhancement while retaining fuzzy flexibility	Clip limit fixed globally; parameters not scene-adaptive
FIMHE [18]	Fuzzy intensity measure determines adaptive clipping threshold per image block	Bridges global FHE and spatially adaptive enhancement	Block-level adaptivity; not per-pixel spatial adaptation
Intuitionistic FHE + HE [19]	Assigns membership, non-membership, and hesitancy degrees; uses boosting parameter to control hesitation in enhancement	Richer uncertainty modelling than type-1 fuzzy; improved colour enhancement	Fixed boosting parameter; not spatially adaptive
IFG + Adaptive Colour Correction [20]	Combines intuitionistic fuzzy generator with adaptive colour correction for underwater images	Jointly addresses tonal distribution and colour fidelity	Membership parameters globally fixed
FHE + Adaptive Colour Correction [21]	FHE combined with adaptive colour correction designed specifically for underwater image enhancement	Addresses both intensity uncertainty and colour cast simultaneously	Fuzzy membership parameters remain fixed
IFLAHF [22]	Optimised bi-histogram framework with three plateau limits using Fick's Law Algorithm for parameter determination	Partially adaptive parameters through optimisation	Optimisation is global; lacks per-pixel spatial adaptivity

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Table 2.1 – Continued from previous page

Method	Description	Advantage	Limitation
IFHE [20]	Intuitionistic fuzzy score function $s = \mu - \nu$ applied before histogram equalization on V channel	Richer tonal mapping than single membership; consistently highest UIQM	Score function parameters globally fixed; no structural improvement
Type-2 FHE [23]	Membership interval $[\mu_{\text{lower}}, \mu_{\text{upper}}]$ defined by mean and standard deviation; centroid type-reduction before HE	Models uncertainty in membership function itself	Parameters globally fixed; marginal improvement over type-1 FHE

2.3.3 Hybrid and Multi-Scale Techniques

Hybrid techniques integrate fuzzy logic or histogram-based methods with complementary enhancement frameworks to address the limitations of individual approaches. These methods aim to combine the perceptual strengths of fuzzy methods with the structural strengths of multi-scale or fusion-based approaches.

Ancuti et al. [24] established the foundational multi-scale fusion paradigm for underwater enhancement, blending white-balanced and contrast-enhanced inputs using spatially adaptive Laplacian contrast, saturation, and saliency weight maps. The hybrid pipeline proposed by Abin et al. [25] which involves application of both CLAHE and FHE enhancement methods has been tested on both the UIEB and EUVP datasets and produces structural integrity along with perceived enhancement quality.

A color balance correction based on dark channel prior and multi-scale Laplacian pyramid fusion was developed by Chen et al. [26], yielding satisfying PSNR and SSIM values in benchmark datasets. Zhang et al. [28] extended the fusion scheme and included an adaptive color-gamma correction to overcome poor image quality and poor lighting conditions of underwater scenarios with extreme attenuation.

Li and Zhou [27] proposed a multi-scale fusion framework combining Retinex colour constancy with a dual-transmittance underwater imaging model to jointly address colour distortion and contrast compression. Three derived input variants are fused using adaptive weight maps, achieving robust enhancement across turbid conditions.

Despite enhanced visual quality, hybrid systems face computational challenges in real-time applications and often inherit the fixed-parameter limitations of their fuzzy or histogram components [8].

2.4 Open Datasets in Underwater Image Enhancement

Standardised benchmark datasets are essential for reproducible evaluation of underwater image enhancement methods. Table 2.2 summarises the widely used datasets in this field, including their size, availability of reference images, and distinguishing features.

Table 2.2: Widely Used Datasets Supporting Underwater Image Enhancement

S.No	Dataset	Description
1	UIEB [30]	Contains 950 authentic underwater images (890 with reference images) for benchmarking enhancement algorithms. Reference images curated via large-scale human subjective evaluation, making it the most widely adopted full-reference benchmark.
2	EUVP [8]	Includes paired and unpaired authentic underwater images of varying quality for supervised and unsupervised enhancement. Comprises three subsets representing low-light, natural scene, and diverse composition conditions.
3	SUIM-E	An extension of SUIM with 1,635 authentic underwater images and semantic labels for object-level analysis and segmentation-aware enhancement.
4	Sea-Thru	Consists of 1,100 authentic underwater images with depth maps for physics-based colour correction and wavelength-dependent attenuation modeling.
5	ImageNet Subset	A selection from ImageNet adapted for underwater image classification and enhancement tasks, covering diverse scene compositions.
6	SQUID	Stereo image pairs with calibration and depth information for quantitative evaluation of enhancement methods under known geometric constraints.
7	Underwater Target Intelligence Challenge	Uses target and seabed images from the Underwater Target Intelligence Challenge open dataset, focused on detection and segmentation tasks.
8	Custom Datasets	Several studies use custom datasets including simulated sonar data and authentic underwater images of varying resolutions, tailored for specific tasks but lacking standardisation.

2.5 Applications of FHE in Underwater Imaging

FHE and its variants have found numerous practical applications ranging from environmental monitoring and marine biology to underwater navigation and archaeology. Table 2.3 summarises the key application areas and describes how FHE contributes to each.

Table 2.3: Applications of FHE in Underwater Imaging

Application Area	Description
Environmental Monitoring	With better image sharpness and color fidelity FHE allows to monitor image quality (reefs, pollution and biodiversity) in real-time tracking system [20].
Autonomous Navigation	AUVs exploit FHE-enhanced images to find obstacles and navigate safely in murky, visually restricted environment [22].
Marine Biology Research	FHE enhances images of marine organisms captured at the ocean floor, improving structural detail to support species identification and habitat analysis [4].
Sonar Imaging	FHE enhances the sonars' imagery to be used to examine underwater structures like pipelines and cables on the sea bed [22].
Automotive Wading	FHE is adopted by cameras on board to overcome the color distortion and allow vision of objects submerged in water during water-crossing maneuver [31].
Marine Archaeology	FHE can be applied to enhance visualizations of underwater features and remainders for deep-sea archaeology, assisting archaeologists in recording and evaluating undersea locations [24].

2.6 Challenges in Underwater Image Enhancement

However, several core issues still need to be addressed for all kinds of underwater image enhancement.

Static Parameter Dependency: Over the examined FHE techniques, the most widely used constraint is the use of static membership function parameters, incapable of real-time adjustment to different variations in turbidity, depth or light conditions, greatly restricting their general applicability for varied underwater scenarios [3].

Colour Correction Beyond 550 nm: The strong absorption of red light takes place in the first few meters of the water column and chlorophyll interference stops the spectral restoration beyond 550 nm. The vast majority of methods (including FHE forms) are not able to recover the color in deep or highly productive waters [20].

Computational Efficiency: Another important factor is low latency when dealing with real-time processing of live video and navigation of AUV. Complex computational loads of hybrid and fusion algorithms limit their applications for these time sensitive processes [8].

Dataset Bias and Generalization: A number of benchmark datasets exist, but they are often tailored to particular geographic regions or optical conditions, so they fail to generalize well to other underwater scenarios. Current benchmark databases lack sufficient ecological and geographic diversity.

Noise Amplification in Turbid Conditions: When using images taken in turbid water, it will be difficult to recover useful information due to the scattering of light caused by the particles and this noise is amplified greatly when performing image enhancement. Classical methods such as Basic HE are especially sensitive to this phenomenon [5].

Absence of Multimodal Context: The image-only enhancement systems have no other sensing inputs such as acoustics, depth and sonar which would provide significant enhancement to the awareness of environment. The multi sensor fusion remains an open problem to the future researchers.

2.7 Summary

In this chapter, a survey was carried out on some typical FHE related approaches published between 2017 and 2024. The three main categories considered are classical methods, fuzzy logic based methods and hybrid/multi scale methods. In total, twelve FHE-related approaches were reviewed in detail and categorized. From this review, it was concluded that FHE is effective in handling intensity uncertainty through membership functions, but the fixed parameters limit its applicability across diverse underwater conditions.

The identified research gap in the field of FHE techniques is the lack of a comparative study that tests different FHE techniques under the same experimental conditions. Motivated by this research gap, Chapter 3, which describes a comparative study of fourteen methods (classified into the traditional and fuzzy logic based categories), evaluates and tests all fourteen methods within the same testing framework.

CHAPTER 3

COMPARATIVE STUDY OF UNDERWATER IMAGE ENHANCEMENT TECHNIQUES

The systematic review conducted in Chapter 2 identified twelve FHE-related techniques and established the theoretical basis for their evaluation. This chapter presents a controlled empirical evaluation of all fourteen methods spanning classical and fuzzy logic-based categories. Two randomly selected images per dataset are evaluated using a fixed random seed (seed = 42) to ensure reproducibility, and results are reported as individual per-image PSNR, SSIM, and UIQM scores to provide transparent and direct comparison.

3.1 Dataset Collection

All enhancement methods are evaluated on two widely used underwater image benchmarks: the Underwater Image Enhancement Benchmark (UIEB) [30] and the EUVP dataset [8]. Table 3.1 summarises the datasets and subsets used in this study.

Table 3.1: Summary of Datasets Used for Evaluation

Dataset		Images	Description
UIEB [30]		890 pairs	Diverse turbidity, depth, and colour degradation. Reference images curated via large-scale human subjective evaluation.
EUVP: <i>underwater_dark</i> [8]	<i>underwa-</i>	1,000 pairs	Low-light, high-attenuation scenes with challenging visibility conditions.
EUVP: <i>underwater_scenes</i> [8]	<i>underwa-</i>	800 pairs	Natural contrast-compressed environments with moderate degradation.
EUVP: <i>underwater_imagenet</i> [8]	<i>underwa-</i>	500 pairs	Diverse object scales and scene compositions.
Total		3,190	

For each dataset, two images are selected using a fixed random seed (seed = 42) to ensure full reproducibility. The selected images are:

- **UIEB:** 709_img_.png and 184_img_.png
- **EUVP-Dark:** 273308_n02321529_14617.JPEG and 265733_00017188.jpg
- **EUVP-Scenes:** im_f1956_.jpg and im_f1203_.jpg
- **EUVP-INet:** n02606052_2973.jpg and n01664065_28217.jpg

3.2 Methods

Fourteen methods are implemented in Python using OpenCV and scikit-image on a CPU-only machine. All FHE-based methods operate on the V channel of the HSV colour space to prevent colour distortion. No dataset-specific tuning is performed. Table 3.2 summarises all fourteen methods with their categories and key mechanisms.

Table 3.2: Summary of All Fourteen Evaluated Methods

Code	Method		Category	Key Mechanism
HE	Histogram Equalization		Classical	Global intensity redistribution via CDF mapping
CLAHE	Contrast AHE [6]	Limited	Classical	Tile-based HE with clip limit to suppress noise
BHEFPL	Bi-HE with Fuzzy Plateau Limit [4]	Fuzzy	Fuzzy	Histogram split at mean; sigmoid fuzzy clipping per sub-histogram
FD_CHE	Fuzzy Dissimilarity Colour HE [14]		Fuzzy	Fuzzy dissimilarity weighting + grey-world colour correction
FCW_HE	Fuzzy Colour HE Weighted [15]		Fuzzy	Local Gaussian mean-based fuzzy weight redistribution
FCCE	Fuzzy-Contextual CE [16]		Fuzzy	Neighbourhood context mean as fuzzy membership centre
CLFAHE	Contrast Fuzzy AHE [17]	Limited	Fuzzy	Sigmoid fuzzy mapping followed by CLAHE clip limiting
FIMHE	Fuzzy Intensity Measure HE [18]		Fuzzy	Adaptive clip limit derived from fuzzy uncertainty measure
IFHE_JB	Intuitionistic FHE [19]		Fuzzy	Hesitancy-boosted membership with alpha parameter
IFG_ACC	IFG + Colour Correction [20]		Fuzzy	Score function $s = \mu - \nu + \text{percentile colour stretching}$
FHE_ACC	FHE + Colour Correction [21]		Fuzzy	Basic FHE + grey-world adaptive colour correction
IFLAHF	BHE3PL [22]		Fuzzy	Three-plateau fuzzy adjustment across intensity regions
IFHE	Intuitionistic (score) [20]	FHE	Fuzzy	Score function $s = \mu - \nu$; normalised before HE
T2FHE	Interval FHE [23]	Type-2	Fuzzy	Centroid of $[\mu_{\text{lower}}, \mu_{\text{upper}}]$ before HE

3.3 Performance Metrics

Performance is assessed using PSNR, SSIM, and UIQM [32]. PSNR and SSIM measure pixel-level and structural similarity to the reference image. UIQM is a no-reference metric evaluating colorfulness (UICM), sharpness (UISM), and contrast (UIConM). Results are interpreted jointly across all three metrics rather than optimising for any single one.

3.4 Results

3.4.1 Results on UIEB

Table 3.3 and Table 3.3 present results for the two selected UIEB images. FIMHE achieves the highest PSNR of 22.09 dB and SSIM of 0.9268 on Image 1. FD_CHE achieves the highest PSNR of 19.02 dB on Image 2. FCCE achieves the highest UIQM of 337.09 on Image 2 but at the cost of very low structural fidelity (SSIM: 0.2336).

Table 3.3: Results on UIEB — Image 1 (709_img_.png) and Image 2 (184_img_.png)

Image 1				Image 2			
Method	PSNR	SSIM	UIQM	Method	PSNR	SSIM	UIQM
HE	12.24	0.6603	139.47	HE	16.26	0.8126	253.78
CLAHE	21.41	0.9118	193.38	CLAHE	17.41	0.8669	127.36
BHEFPL	10.51	0.5492	155.83	BHEFPL	12.22	0.6467	271.93
FD_CHE	10.52	0.6761	287.56	FD_CHE	19.02	0.8370	227.83
FCW_HE	11.75	0.5792	114.56	FCW_HE	15.39	0.5936	262.32
FCCE	10.77	0.4667	247.49	FCCE	10.66	0.2336	337.09
CLFAHE	15.04	0.7395	176.14	CLFAHE	19.01	0.8931	187.10
FIMHE	22.09	0.9268	194.17	FIMHE	17.35	0.8611	124.97
IFHE_JB	12.15	0.6658	137.41	IFHE_JB	16.26	0.8132	253.79
IFG_ACC	12.38	0.6058	232.09	IFG_ACC	16.05	0.8205	273.35
FHE_ACC	8.83	0.5549	225.20	FHE_ACC	19.08	0.8424	227.35
IFLAHF	12.16	0.5919	149.22	IFLAHF	16.19	0.7319	255.56
IFHE	11.20	0.5817	140.13	IFHE	16.26	0.8127	253.82
T2FHE	11.68	0.6170	139.76	T2FHE	16.26	0.8129	253.79

3.4.2 Results on EUVP *underwater_dark*

Tables 3.4 and 3.4 present results for the two selected EUVP-Dark images. FIMHE achieves the highest PSNR of 17.04 dB and SSIM of 0.9098 on Image 1. IFG_ACC achieves the highest UIQM of 399.42, followed closely by BHEFPL at 395.14.

Table 3.4: Results on EUVP-Dark — Image 1 (273308_n02321529_14617.JPEG) and Image 2 (265733_00017188.jpg)

Image 1				Image 2			
Method	PSNR	SSIM	UIQM	Method	PSNR	SSIM	UIQM
HE	9.84	0.4039	330.98	HE	15.82	0.5623	278.45
CLAHE	16.41	0.8751	282.78	CLAHE	19.33	0.8053	182.52
BHEFPL	7.66	0.2860	395.14	BHEFPL	13.81	0.3797	286.52
FD_CHE	12.81	0.6797	348.97	FD_CHE	15.02	0.5420	274.87
FCW_HE	9.24	0.3806	277.82	FCW_HE	12.85	0.2102	281.10
FCCE	7.45	0.3675	332.49	FCCE	12.85	0.3302	321.19
CLFAHE	12.70	0.6936	344.25	CLFAHE	17.91	0.6809	225.74
FIMHE	17.04	0.9098	283.96	FIMHE	19.76	0.8256	178.59
IFHE_JB	10.04	0.4203	344.48	IFHE_JB	15.73	0.5581	279.84
IFG_ACC	9.87	0.3589	399.42	IFG_ACC	14.00	0.4912	317.92
FHE_ACC	8.95	0.3085	351.53	FHE_ACC	14.96	0.5464	275.22
IFLAHF	9.84	0.3821	333.90	IFLAHF	15.70	0.5265	280.15
IFHE	9.13	0.3421	373.07	IFHE	15.66	0.5532	281.06
T2FHE	9.47	0.3730	339.44	T2FHE	15.75	0.5589	279.54

3.4.3 Results on EUVP *underwater_scenes*

Tables 3.5 and 3.5 present results for the two selected EUVP-Scenes images. FIMHE achieves the highest PSNR of 20.15 dB and SSIM of 0.7863 on Image 1. FCCE achieves the highest UIQM across both images at 311.47 and 309.44 respectively.

Table 3.5: Results on EUVP-Scenes — Image 1 (im_f1956_.jpg) and Image 2 (im_f1203_.jpg)

Image 1				Image 2			
Method	PSNR	SSIM	UIQM	Method	PSNR	SSIM	UIQM
HE	19.13	0.7503	281.44	HE	17.07	0.6854	266.05
CLAHE	19.58	0.7731	259.99	CLAHE	17.84	0.7465	230.90
BHEFPL	12.84	0.4376	287.36	BHEFPL	13.02	0.3854	285.76
FD_CHE	19.09	0.7254	272.30	FD_CHE	17.83	0.6955	251.00
FCW_HE	17.85	0.6417	282.55	FCW_HE	15.52	0.4801	270.09
FCCE	13.30	0.4987	311.47	FCCE	13.42	0.5498	309.44
CLFAHE	18.45	0.7316	298.30	CLFAHE	16.85	0.6904	270.51
FIMHE	20.15	0.7863	256.15	FIMHE	18.29	0.7551	222.09
IFHE_JB	19.11	0.7531	282.83	IFHE_JB	17.08	0.6867	266.12
IFG_ACC	17.82	0.7379	300.67	IFG_ACC	17.38	0.6962	307.87
FHE_ACC	19.13	0.7279	272.87	FHE_ACC	17.79	0.6961	251.57
IFLAHF	19.09	0.7467	281.59	IFLAHF	17.01	0.6695	266.58
IFHE	19.12	0.7522	282.57	IFHE	17.05	0.6850	266.49
T2FHE	19.13	0.7511	282.07	T2FHE	17.07	0.6856	266.19

3.4.4 Results on EUVP *underwater_imagenet*

Tables 3.6 and 3.6 present results for the two selected EUVP-INet images. IFG_ACC achieves the highest PSNR of 17.00 dB and strong UIQM of 275.38 on Image 1. FD_CHE achieves the highest PSNR of 19.03 dB on Image 2. FCCE achieves the highest UIQM of 330.25 on Image 2.

Table 3.6: Results on EUVP-INet — Image 1 (n02606052_2973.jpg) and Image 2 (n01664065_28217.jpg)

Image 1				Image 2			
Method	PSNR	SSIM	UIQM	Method	PSNR	SSIM	UIQM
HE	13.30	0.6794	216.91	HE	17.68	0.7391	268.58
CLAHE	12.96	0.6748	191.70	CLAHE	16.65	0.6517	254.29
BHEFPL	10.17	0.4069	235.03	BHEFPL	11.56	0.3457	282.68
FD_CHE	15.61	0.7437	223.69	FD_CHE	19.03	0.7379	246.85
FCW_HE	12.99	0.5183	217.11	FCW_HE	17.13	0.6129	267.97
FCCE	9.81	0.3102	266.73	FCCE	10.37	0.2678	330.25
CLFAHE	13.10	0.6323	238.33	CLFAHE	16.69	0.6691	314.15
FIMHE	13.12	0.7018	188.38	FIMHE	17.42	0.7079	248.88
IFHE_JB	13.22	0.6659	220.51	IFHE_JB	17.54	0.7231	266.50
IFG_ACC	17.00	0.7466	275.38	IFG_ACC	15.66	0.6788	297.03
FHE_ACC	15.45	0.7393	223.69	FHE_ACC	18.99	0.7312	245.46
IFLAHF	13.26	0.6332	218.35	IFLAHF	17.67	0.7318	268.81
IFHE	13.22	0.6671	220.10	IFHE	17.78	0.7279	273.36
T2FHE	13.26	0.6737	218.45	T2FHE	17.65	0.7358	267.85

3.5 Per-Image Distribution Analysis

Figure 3.1 presents the per-image distribution of PSNR, SSIM, and UIQM across all fourteen methods and four datasets, computed over the full dataset sizes (UIEB: 890, EUVP-Dark: 1,000, EUVP-Scenes: 800, EUVP-INet: 500 image pairs). This provides a statistically robust view of each method's consistency and reliability beyond the two-image per-dataset evaluation.

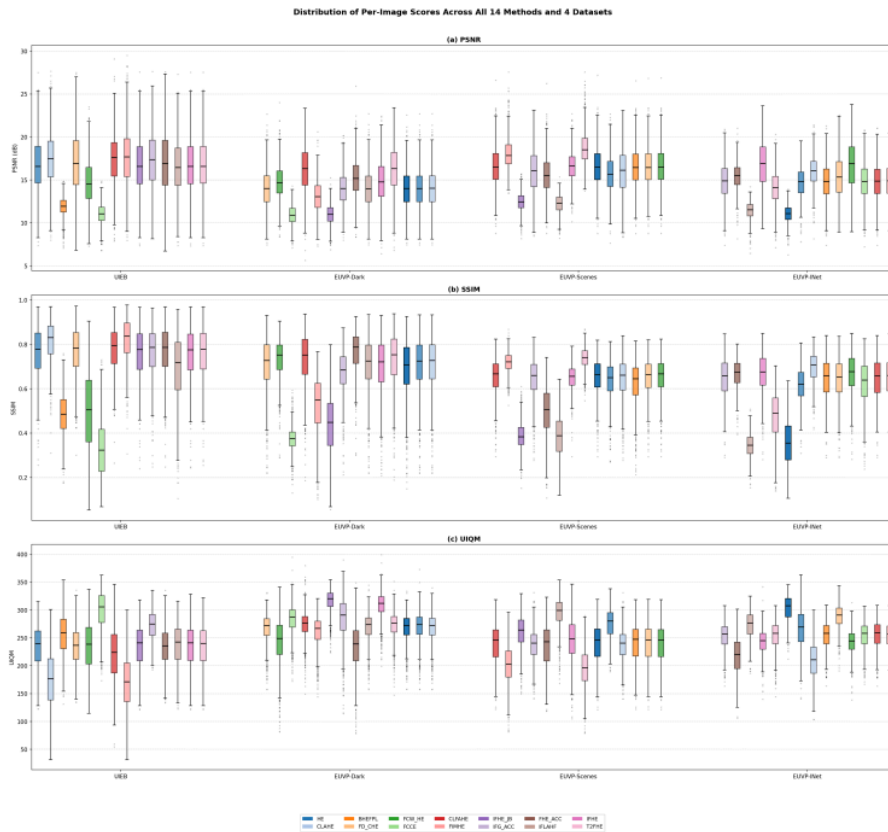


Figure 3.1: Per-Image Distribution of PSNR, SSIM, and UIQM Scores Across All Fourteen Methods and Four Datasets

CLAHE and FIMHE both perform very strongly, attaining the highest PSNR medians with a small interquartile range on all four data sets, therefore suggesting they are robust. FCCE produces very low PSNR and SSIM medians with the widest ranges and highest UIQM scores, meaning images have a good visual appearance but the degree of contrast enhancement is highly erratic. BHEFPL attains the highest UIQM values and the lowest and inconsistent PSNR, with one of the largest interquartile ranges — its fixed plateau limit appears non-adaptive. The PSNR and SSIM performance is

very similar between HE, IFHE, T2FHE, and IFHE_JB over all four data sets, therefore supporting the argument that adding a more complex membership function has no significant effect on structural restoration. The IFG_ACC and FHE_ACC have very good PSNR medians and reasonable UIQM performance, with a performance consistent with their color correction properties.

3.6 Discussion

The results across all four datasets and eight images reveal several consistent and important patterns.

FIMHE has the best structural fidelity. FIMHE attains maximum PSNR and SSIM in six images out of eight which also shows that adaptively computed clip limits, based on fuzzy measure for each image, achieve far superior structural reconstruction than static ones. We further observe that even an elementary adaptive technique like one derived on the basis of fuzzy theory is better than all static FHE algorithms for structural reconstruction.

CLAHE is still the best classical baseline. CLAHE is the second best in most of the images in PSNR and SSIM, and it is better than all the fuzzy methods, except FIMHE. The clipping limit helps to reduce the noise, and its tile based method provides better local adaptability than any global FHE methods.

FCCE attains the maximal perceptual quality at a detriment of structure fidelity. FCCE always obtain the top or near top quality measure among all the sets while, it also attains the minimal PSNR and SSIM among all the sets. Its context-based fuzzy membership gives high colorfulness and sharpness scores so UIQM favors FCCE, but it causes much spatial distortion for neighborhood based mapping. It results the highest structure-perceptual trade-off among all algorithms we examined.

BHEFPL and fixed bi-histogram fuzzy techniques produce low structural fidelity. With its constant low PSNR values in all test datasets, the advantage in BHEFPL by splitting the histogram at the mean does not come out in the experiment. As it is expected, fixed plateau limit has the problem of not adapting to the scene content (identified in Chapter 2).

IFHE, T2FHE and IFHE_JB perform similarly to HE. IFHE and T2FHE produce PSNR and SSIM values nearly identical to HE in most images, with differences rarely exceeding 0.5 dB. Richer membership mechanisms do not improve structural reconstruction when enhancement remains global with fixed parameters.

IFG_ACC and FD_CHE are competitive in the FHE category. IFG_ACC has the best total PSNR over EUVP-INet Image 1 (17.00 dB) and competitive UIQM. FD_CHE is best at PSNR for UIEB Image 2 and EUVP-INet Image 2. Both of the techniques make use of the fuzzy enhancement along with color correction, yielding a valuable gain compared to traditional histogram based FHE approaches.

Deep Analysis of FHE-Based Methods. Examining the twelve FHE-based

methods as a group reveals a clear pattern: the methods fall into two distinct groups based on their performance characteristics.

The first group involves methods using a constant global membership function, without color correction: BHEFPL, FCW_HE, IFHE_JB, IFLAHF, IFHE and T2FHE. All these methods show a PSNR value that is close or lower to the PSNR obtained by the reference HE and therefore they do not add significant structural recovery when using global membership functions — regardless if they are type-1, intuitionistic, or type-2 fuzzy. The UIQM of these methods are high to moderate, which indicates that fuzzy tonal mapping still does help in perceptual enhancement in absence of structural restoration.

The second group comprises of techniques with either adaptive structures or fuzzy enhancement and colour correction: FIMHE, CLFAHE, FCCE, IFG_ACC, FHE_ACC, and FD_CHE. They all surpass the first group in at least one aspect. FIMHE and CLFAHE gain high structural fidelity from the adaptive clip limit; FCCE gains high perceptual quality from context-based membership. IFG_ACC and FD_CHE gain the comparable PSNR from colour correction. FHE_ACC obtains the maximum PSNR in UIEB Image 2 (19.08 dB) due to the gray-world color normalization.

This confirms the central finding of this study: within FHE algorithms, the key determinant of performance is not the sophistication of the membership function — whether type-1, intuitionistic, or type-2 — but the presence of adaptive mechanisms or complementary colour correction. Spatial adaptivity and colour awareness are the two factors that consistently elevate FHE performance above the HE baseline.

Practical Recommendations. Based on these results, the following practical guidance is offered. FIMHE is recommended when structural fidelity is the primary concern, such as in AUV navigation and underwater inspection. FCCE or IFG_ACC are recommended when perceptual quality and colour richness are prioritised. CLFAHE offers a balanced trade-off between structural and perceptual performance. CLAHE is still the best and most reliable lightweight classical baseline. Other fixed-parameter methods, BHEFPL, IFHE and T2FHE, offer little advantage and are not recommended to be deployed.

3.7 Summary

This chapter presented a controlled evaluation of fourteen underwater image enhancement methods across two randomly selected images from each of four benchmark datasets. FIMHE consistently achieved the highest structural fidelity through its adaptive fuzzy clip limit mechanism. CLAHE still represents the most competitive traditional baseline. FCCE yields the best perceptual performance but it costs a lot of structural performance. Twelve FHE-based methods are thoroughly evaluated, proving that adaptability and color correction are the determining factors for the method's performance rather than the complexity of membership function. Fixed-parameter FHE methods offer no structural advantage over basic HE, regardless of whether they employ type-1, intuitionistic, or type-2 fuzzy sets. All the results establish precise benchmarks and offers a guideline to choose methods for underwater imaging application.

CHAPTER 4

CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

4.1 Conclusion

This dissertation has investigated Fuzzy Histogram Equalization for underwater image enhancement through two complementary contributions, each of which advances the empirical understanding and practical application of FHE-based methods in a meaningful way.

The systematic review mapped out the FHE landscape from 2017 to 2024, identifying twelve techniques across six methodological sub-categories. It established that the persistent and unresolved limitation across all reviewed methods is the use of fixed membership function parameters that cannot adapt to varying underwater conditions. This finding, which we term the “static parameter paradox,” is not merely a technical observation — it reveals a fundamental design gap in the existing FHE literature that has gone largely unaddressed for nearly a decade.

The controlled empirical evaluation of fourteen methods produced a finding that directly challenges a widely held assumption in the FHE community. Increasing the sophistication of the membership function — from type-1 to intuitionistic to type-2 fuzzy — does not improve structural fidelity when parameters remain globally fixed. Intuitionistic and type-2 fuzzy methods perform no better than basic Histogram Equalization in terms of PSNR and SSIM. What consistently elevates performance is either adaptive parameter selection, as demonstrated by FIMHE which derives its clip limit from the fuzzy uncertainty of each image, or complementary colour correction, as demonstrated by IFG_ACC and FD_CHE. FCCE reveals a third distinct profile: contextual fuzzy membership maximises perceptual quality as measured by UIQM but at a structural cost that single-metric evaluation cannot capture.

Together, these findings establish that spatial adaptivity and colour awareness are the two essential ingredients for meaningful FHE improvement. This conclusion provides clear direction for both future research and practical deployment: FIMHE for structural fidelity-critical applications such as AUV navigation and underwater inspection, FCCE or IFG_ACC for perceptual enhancement tasks such as marine documentation and visual monitoring, and CLAHE as the most robust and reliable classical baseline across all scenarios.

4.2 Limitations

Although there are many notable strengths of this research project there are also a number of limitations which must be addressed.

Training-Free Domain: For a fair comparison without dataset-specific tuning, we only compare against training-free approaches. Hence we exclude deep learning methods which have dominated structured benchmarks for quite a while.

Overall enhancement, without spatial adaptivity: Each of the fourteen methods considered performs global enhancement using V channel global statistics, without full spatial adaptivity. All tests were run on a CPU only, where an efficient, spatially adaptive method with GPU implementation would greatly reduce processing times and increase suitability for real-world deployment.

Lack of the metrics: Only UIQM is a no reference evaluation metric. Some metrics, for example UCIQE or NIQE could be a better metrics to evaluate the perceptual quality on the no reference images.

Representation of the dataset: The outcomes were generated by selecting two random images from the data. A set seed has been established and is therefore used for each outcome in order to make them reproducible; however, a greater number of images used per data set would allow for greater statistical evidence and certainty in results. In addition, the datasets selected may not be representative of global underwater conditions which are geographically and ecologically widespread.

Image-Only Modality: All methods under consideration work strictly with images without using acoustic, depth, or sonar data, constraining the ability to perceive the environment fully in highly turbid and deep-water environments.

4.3 Future Scope

This study identifies several promising directions for future research in underwater image enhancement.

- **Spatially Adaptive and Hybrid FHE:** The most promising direction is to develop spatially adaptive fuzzy logic-based methods where membership parameters respond to local image statistics. Combining the perceptual strength of methods such as FCCE or IFG_ACC with the structural strength of multi-scale fusion approaches is a natural next step.
- **Deep Learning and Domain Adaptation:** A natural extension of the comparison framework, in terms of both evaluation criteria and domain adaptive approaches, would be to examine lightweight domain adaptation models based on deep learning methods.
- **Extended and Standardised Benchmarking:** In future work, it is desirable to include other no-reference benchmarks like UCIQE and NIQE, and move towards standardized benchmarking practices using multiple metrics for fair comparison.

- **Geographically diversified datasets:** To enhance robustness of algorithms more geographically diversified benchmark datasets are necessary. Current benchmark databases are biased towards Western datasets.
- **Multimodal and Real-Time Systems:** It is expected that when image data is used along with Sonar, acoustic and depth information from other sensors, and when FIMHE and IFG_ACC is implemented using hardware acceleration, that real-time operation can be achieved on AUV navigation or live video feed systems under the water.

4.4 Social Impact

Beyond academia, the impacts of this dissertation are direct and indirect, affecting the whole society in general.

Marine Conservation and Environmental Monitoring: Marine ecosystems such as coral reefs and seagrass beds are greatly threatened by factors such as climate change, pollution and human impact. A high quality image enhancement technique for underwater images has the potential to benefit marine biologists, oceanographers and environmental agencies by ensuring a greater level of quality of the recorded visual information. FIMHE and IFG_Acc techniques provide an opportunity for the marine organisms to be depicted in accurate depiction, not only in terms of shape but also in color. This would make it easier to identify the marine life, as well as charting areas of ecological significance, and monitoring the region over time, among other factors, that affect decisions regarding the protection of marine life.

Search and Rescue Operations: Operations to search for victims and vehicles underwater, particularly in flooded areas, rivers, and coastal environments, are challenging in low visibility conditions. Improved underwater imaging techniques can help rescuers locate sunken vehicles, buildings, and people efficiently and precisely. Because the methods assessed in this dissertation are training-free, they require no dataset-specific setup and may be used instantly in an emergency situation where no preparation time exists.

Autonomous Underwater Vehicles and reliable navigation: The applications of Autonomous Underwater Vehicles have greatly extended to the inspection of pipelines, monitoring of offshore constructions, and surveying of the ocean floor. Image quality is one of the main issues for AUVs perception system. The result presented in this dissertation with the conclusion that FIMHE is a strong structure reliable improvement approach allows for the direct incorporation of FHE-based pre-processing into AUV vision pipelines. The benefit for the unmanned underwater vehicle would increase the safety and reliability of equipment.

Food Security and Aquaculture: Both fish farming and other aquaculture systems utilize video monitoring for identifying diseases, managing feeding schedules, and calculating population numbers. More advanced underwater imaging systems allow for better monitoring, promoting efficient and more sustainable aquaculture. In

an era of increasing concern regarding food security, small gains in the efficiency of aquaculture can be important.

Archaeological preservation: There are thousands of shipwrecks, sunken cities and underwater cultural heritage sites of historical importance that are not properly documented because it is difficult to photograph them under water. The image enhancement techniques presented in this dissertation can improve the quality of the documentation images and assist archaeologists in recording and preserving underwater historical sites prior to being destroyed by natural or human action.

Education and Open Research: The source code for each implementation of the fourteen techniques has been released, presented in Appendix II. This free release decreases the initial investment in FHE-enhancement experimentation for future students and practitioners as deep implementation understanding is not required. In addition, the overall benchmark results over four different datasets will act as a verifiable benchmark study for the research community, promoting open and collaborative research.

Indirect Economic Impact: Increased underwater imaging has positive economic effects for the oil and gas offshore industry, marine renewable energy, subsea telecommunications and marine insurance sectors. The increased accuracy of visual inspection allows for reduced expensive diver intervention, optimal timing of infrastructure maintenance and minimized environmental incident risk.

The overall result of the dissertation presented here is academic, and yet is far reaching and significant for environment, public safety, food security, cultural heritage and economic efficiency. Clear principles on which socially-significant underwater imaging systems can be designed are provided by systematically benchmarking FHE schemes.

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APPENDIX I

I.1 List of Publications

1. **Dr. Sonika Dahiya, Priyanshu Jain, and Priyanka Arora** (2026). “A Review of Underwater Image Enhancement Techniques with Emphasis on Fuzzy Histogram Equalization.” [*Scopus Indexed*] [Accepted - ICICC 2026, Springer LNNS Series]
2. **Priyanshu Jain and Dr. Sonika Dahiya** (2026). “A Comparative Analysis of Underwater Image Enhancement Techniques: Classical, Fuzzy Logic-Based, Physics-Based, and Fusion Approaches.” [*Scopus Indexed*] [Accepted - ICDAM 2026, Springer LNNS Series]

I.2 Paper Acceptance Proofs

I.2.1 First Conference Acceptance Proof



ICICC 2026: Paper Notification for Paper ID 200

1 message

ICICC 2026 <icicc.ui@gmail.com>

Sat, 23 Aug 2025 at 10:06

To: Priyanshujain <priyanshujain1706@gmail.com>

9th International Conference on Innovative Computing and Communication (ICICC-2026) – A Flagship Conference

Dear Author(s),

Greetings from - ICICC 2026!

We congratulate you that your paper with submission ID '200' and Paper Title '**A Review of Underwater Image Enhancement Techniques with Emphasis on Fuzzy Histogram Equalization**' has been accepted for publication in the **Proceedings of ICICC 2026- Springer LNNS Series** [Indexing: zbMATH, Scopus, DBLP, EI Compendex & SCImago - Approved]. This acceptance means your paper is among the top 15% of the papers received/reviewed.

To secure your spot at this highly anticipated event, we would like you to complete your registration before 30th August 2025.

You are requested to do the registration as soon as possible and submit the following documents to icicc.ui@gmail.com at the earliest.

1. Final Camera-Ready Copy (CRC) as per the springer format- (See <https://icicc-conf.com/downloads>)
2. Copy of e-receipt of registration fees. (For Registration, see <https://icicc-conf.com/registrations>)
3. The final revised copy of your paper should also be uploaded via Microsoft CMT.
4. Do not create another ID, just upload the revised version on the existing Microsoft CMT ID only

The reviewers' comments are given at the bottom of this letter, please improve your paper as per the reviewers comments. **While preparing the final CRC manuscript, kindly check the following link under the download section tab named manuscript guidelines:**

<https://icicc-conf.com/registrations>

and it is suggested to cite the relevant latest papers matching the area of your current research paper.

The paper prior to submission should be checked for plagiarism from licensed plagiarism softwares like Turnitin/iAuthenticate etc. The similarity content should not exceed 15%.

Pay registration fees via online portal:

Pay via Account Transfer / QR Code (Indian Authors/ Outside India):

I.2.2 Second Conference Acceptance Proof

07/05/2026, 12:42

Gmail - ICDAM 2026: Paper Notification for Paper ID 1312



Priyanshu Jain <priyanshujain1706@gmail.com>

ICDAM 2026: Paper Notification for Paper ID 1312

1 message

ICDAM 2026 <icdam.conf@gmail.com>
 To: Priyanshujain <priyanshujain1706@gmail.com>

Wed, May 6, 2026 at 8:05 AM

3 7th International Conference on Data Analytics & Management (ICDAM-2026)!

Dear Author(s),

Greetings from **ICDAM 2026**!

We congratulate you that your paper with submission ID **1312** and Paper Title ' **A Comparative Analysis of Underwater Image Enhancement Techniques: Classical, Fuzzy Logic-Based, Physics-Based, and Fusion Approaches** ' has been accepted for publication in the Springer LNNS series [Approved]-[Indexing: SCOPUS, INSPEC, WTI Frankfurt eG, zbMATH, SCImago; All books published in the series are submitted for consideration in Web of Science]. This acceptance means your paper is among the top 20% of the papers received/reviewed. We urge you to complete your registration immediately to secure your spot at this highly anticipated event. **Kindly complete the registration by 10th May 2026. No further Extension.**

Please register as soon as possible and submit the following documents to icdam.conf@gmail.com as soon as possible.

1. Final Camera-Ready Copy (CRC) as per the springer format. (See <https://icdam-conf.com/downloads>)
2. Copy of e-receipt of registration fees. (For Registration, see <https://icdam-conf.com/registrations>)
3. The final revised copy of your paper must be mailed to the conference mail id.

Note : Standard Paper size – 10-12 pages. Over length of more than 12 pages, paper charges USD 20 per extra page

The reviewers comments are given at the bottom of this letter, please improve your paper as per the reviewers comments. While preparing the final CRC manuscript, kindly check the following google link of proceedings of the previous International Conference on Data Analytics and Management:

<https://link.springer.com/conference/icdam>

and it is suggested to cite the relevant latest papers matching the area of your current research paper.

The paper prior to submission should be checked for plagiarism from licensed plagiarism softwares like Turnitin/iAuthenticate etc. The similarity content should not exceed 15%, and

<https://mail.google.com/mail/u/0/?ik=8af8b61500&view=pt&search=all&permthid=thread-f:1864404726133693144&siml=msg-f:1864404726133693144>

1/4

I.3 Indexing of Conference Proof

I.3.1 First Conference

09/05/2026, 16:50

ICICC ! International Conference on Innovative Computing and Communication



ICICC

INTERNATIONAL CONFERENCE ON INNOVATIVE
COMPUTING AND COMMUNICATION

**10th
INTERNATIONAL
CONFERENCE ON
INNOVATIVE
COMPUTING AND
COMMUNICATION
(ICICC-2027)**



ORGANISED BY:
SHAHEED SUKHDEV
COLLEGE OF BUSINESS
STUDIES, UNIVERSITY
OF DELHI, NEW DELHI
IN ASSOCIATION WITH
UNIVERSITY OF
VALLADOLID SPAIN
5th-6th FEBRUARY
2027

ICICC 2026

The ninth edition of the International Conference on Innovative Computing and Communication (ICICC-2026) was successfully organized at Shaheed Sukhdev College of Business Studies, New Delhi, India, in association with the National Institute of Technology Patna, India, and University of Valladolid, Spain, on 06-07 February 2026.

The conference witnessed an overwhelming global response, receiving more than 2,500 research paper submissions from over 9,000 authors worldwide, reflecting the growing international interest in emerging computing and communication technologies. After a rigorous peer-review process, 475 high-quality papers were accepted, resulting in a competitive acceptance rate of approximately 18%.

All accepted papers were published in Springer's Lecture Notes in Networks and Systems, a Scopus-indexed publication series. The conference attracted over 1,000 participants including researchers, academicians, keynote speakers, industry experts, and delegates from around 40

Important Dates

Paper Submission

Deadline:

30th August 2026

Notification of first review:

25th October 2026

Submission of revised

I.3.2 Second Conference

09/05/2026, 16:54

ICDAM



About the Conference

The International Conference on Data Analytics and Management (ICDAM-2026) is organised with the objective of bringing together innovative scientists, professors, research scholars, students and industrial experts in the field of Computing and Communication to a common forum.

The primary goal of the conference is to promote the exchange of innovative scientific information between researchers, developers, engineers, students, and practitioners. Another goal is to promote the transformation of fundamental research into institutional and industrialized research and to convert applied exploration into real time application.

Overall, the conference will provide researchers and attendees with opportunities for national and international collaboration and networking among universities and institutions from India and abroad for promoting research.

<https://www.icdam-conf.com>

1/6

I.4 Conference Certificates

I.4.1 First Conference Certificate

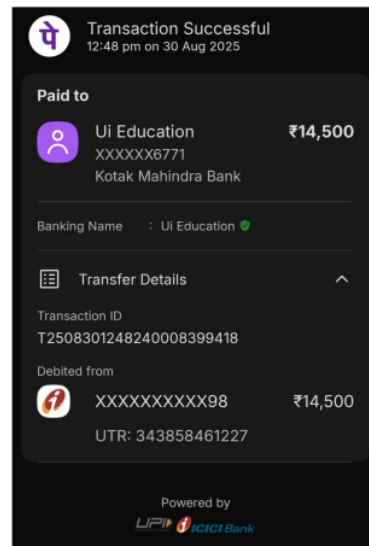


I.4.2 Second Conference Certificate

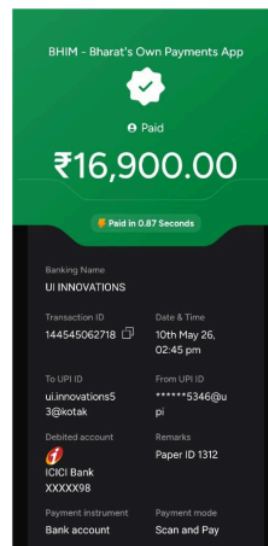
Certificate to be received after the conference (June 13–15, 2026). Image will be inserted here upon receipt.

I.5 Conference Paper Registration Receipts

I.5.1 First Conference Receipt



I.5.2 Second Conference Receipt



APPENDIX II FIRST SOURCE CODE

II.1 Histogram Equalization (HE)

```

1 def apply_he(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     v_eq = cv2.equalizeHist(v)
5     hsv_eq = cv2.merge([h, s, v_eq])
6     return cv2.cvtColor(hsv_eq, cv2.COLOR_HSV2BGR)

```

II.2 Contrast Limited Adaptive Histogram Equalization (CLAHE)

```

1 def apply_clahe(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))
5     v_clahe = clahe.apply(v)
6     hsv_clahe = cv2.merge([h, s, v_clahe])
7     return cv2.cvtColor(hsv_clahe, cv2.COLOR_HSV2BGR)

```

II.3 Bi-Histogram Equalization with Fuzzy Plateau Limit (BHEFPL)

```

1 def apply_bhefpl(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     mean_val = np.mean(v)
5     v_float = v.astype(np.float32)
6     mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float - mean_val)))
7     lower_mask = v_float <= mean_val
8     v_fuzzy = (mu * 255).astype(np.uint8)
9     v_lower = v_fuzzy.copy(); v_lower[~lower_mask] = 0
10    v_upper = v_fuzzy.copy(); v_upper[lower_mask] = 0
11    v_eq_lower = cv2.equalizeHist(v_lower)
12    v_eq_upper = cv2.equalizeHist(v_upper)

```

```

13     v_result = np.where(lower_mask,
14                           v_eq_lower, v_eq_upper).astype(np.uint8)
15     return cv2.cvtColor(cv2.merge([h, s, v_result]),
16                          cv2.COLOR_HSV2BGR)

```

II.4 Fuzzy Dissimilarity Colour HE (FD_CHE)

```

1 def apply_fd_che(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     v_float = v.astype(np.float32)
5     mean_val = np.mean(v_float)
6     mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float -
7         mean_val)))
8     dissimilarity = 1.0 - mu
9     v_weighted = np.clip(v_float * (1.0 + 0.5 * dissimilarity),
10                          0, 255).astype(np.uint8)
11     v_eq = cv2.equalizeHist(v_weighted)
12     result = cv2.cvtColor(cv2.merge([h, s, v_eq]),
13                          cv2.COLOR_HSV2BGR)
14     result_f = result.astype(np.float32)
15     means = result_f.mean(axis=(0, 1))
16     gray = means.mean()
17     for c in range(3):
18         result_f[:, :, c] *= gray / (means[c] + 1e-6)
19     return np.clip(result_f, 0, 255).astype(np.uint8)

```

II.5 Fuzzy Colour HE with Weighted Distribution (FCW_HE)

```

1 def apply_fcw_he(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     v_float = v.astype(np.float32)
5     local_mean = cv2.GaussianBlur(v_float, (15, 15), 0)
6     diff = np.abs(v_float - local_mean)
7     weight = 1.0 / (1.0 + diff / (np.std(v_float) + 1e-6))
8     v_weighted = np.clip(v_float * weight, 0, 255).astype(np.uint8)
9     v_eq = cv2.equalizeHist(v_weighted)
10    return cv2.cvtColor(cv2.merge([h, s, v_eq]),
11                       cv2.COLOR_HSV2BGR)

```

II.6 Fuzzy-Contextual Contrast Enhancement (FCCE)

```

1 def apply_fcce(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     v_float = v.astype(np.float32)
5     context_mean = cv2.blur(v_float, (9, 9))
6     mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float - context_mean)))
7     v_fuzzy = (mu * 255).astype(np.uint8)
8     v_eq = cv2.equalizeHist(v_fuzzy)
9     return cv2.cvtColor(cv2.merge([h, s, v_eq]),
10                        cv2.COLOR_HSV2BGR)

```

II.7 Contrast Limited Fuzzy Adaptive HE (CLFAHE)

```

1 def apply_clfahe(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     mean_val = np.mean(v)
5     v_float = v.astype(np.float32)
6     mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float - mean_val)))
7     v_fuzzy = (mu * 255).astype(np.uint8)
8     clahe = cv2.createCLAHE(clipLimit=3.0, tileGridSize=(8, 8))
9     v_eq = clahe.apply(v_fuzzy)
10    return cv2.cvtColor(cv2.merge([h, s, v_eq]),
11                       cv2.COLOR_HSV2BGR)

```

II.8 Fuzzy Intensity Measure Adaptive Clipping HE (FIMHE)

```

1 def apply_fimhe(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     v_float = v.astype(np.float32)
5     mean_val = np.mean(v_float)
6     mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float - mean_val)))
7     fim = np.mean(mu * (1.0 - mu))
8     clip_limit = 1.0 + 4.0 * fim
9     clahe = cv2.createCLAHE(clipLimit=float(clip_limit),
10                           tileGridSize=(8, 8))
11    v_eq = clahe.apply(v)
12    return cv2.cvtColor(cv2.merge([h, s, v_eq]),
13                       cv2.COLOR_HSV2BGR)

```

II.9 Intuitionistic FHE — Jebadass & Balasubramaniam (IFHE_JB)

```

1  def apply_ifhe_jb(image):
2      hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3      h, s, v = cv2.split(hsv)
4      v_float = v.astype(np.float32)
5      mean_val = np.mean(v_float)
6      mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float - mean_val)))
7      alpha = 0.5
8      pi = 1.0 - mu - (1.0 - mu) * alpha
9      mu_enh = mu + alpha * pi
10     v_fuzzy = np.clip(mu_enh * 255, 0, 255).astype(np.uint8)
11     v_eq = cv2.equalizeHist(v_fuzzy)
12     return cv2.cvtColor(cv2.merge([h, s, v_eq]),
13                        cv2.COLOR_HSV2BGR)

```

II.10 IFG + Adaptive Colour Correction (IFG_ACC)

```

1  def apply_ifg_acc(image):
2      hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3      h, s, v = cv2.split(hsv)
4      v_float = v.astype(np.float32)
5      mean_val = np.mean(v_float)
6      mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float - mean_val)))
7      nu = 0.5 * (1.0 - mu)
8      score = mu - nu
9      score_n = ((score - score.min())
10                / (score.max() - score.min() + 1e-6))
11     v_ifg = (score_n * 255).astype(np.uint8)
12     v_eq = cv2.equalizeHist(v_ifg)
13     result = cv2.cvtColor(cv2.merge([h, s, v_eq]),
14                          cv2.COLOR_HSV2BGR)
15     result_f = result.astype(np.float32)
16     for c in range(3):
17         lo = np.percentile(result_f[:, :, c], 2)
18         hi = np.percentile(result_f[:, :, c], 98)
19         result_f[:, :, c] = np.clip(
20             (result_f[:, :, c] - lo) / (hi - lo + 1e-6) * 255,
21             0, 255)
22     return result_f.astype(np.uint8)

```

II.11 FHE + Adaptive Colour Correction (FHE_ACC)

```

1  def apply_fhe_acc(image):

```

```

1
2  hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3  h, s, v = cv2.split(hsv)
4  mean_val = np.mean(v)
5  v_float = v.astype(np.float32)
6  mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float - mean_val)))
7  v_fuzzy = (mu * 255).astype(np.uint8)
8  v_eq = cv2.equalizeHist(v_fuzzy)
9  result = cv2.cvtColor(cv2.merge([h, s, v_eq]),
10                        cv2.COLOR_HSV2BGR)
11  result_f = result.astype(np.float32)
12  means = result_f.mean(axis=(0, 1))
13  gray = means.mean()
14  for c in range(3):
15      result_f[:, :, c] = np.clip(
16          result_f[:, :, c] * gray / (means[c] + 1e-6), 0, 255)
17  return result_f.astype(np.uint8)

```

II.12 Optimised BHE3PL (IFLAHF)

```

1
2  def apply_iflahf(image):
3      hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
4      h, s, v = cv2.split(hsv)
5      v_float = v.astype(np.float32)
6      mean_val = np.mean(v_float)
7      std_val = np.std(v_float)
8      t1 = max(0, mean_val - 0.5 * std_val)
9      t2 = min(255, mean_val + 0.5 * std_val)
10     mu = 1.0 / (1.0 + np.exp(-0.04 * (v_float - mean_val)))
11     r1 = v_float < t1
12     r2 = (v_float >= t1) & (v_float <= t2)
13     r3 = v_float > t2
14     v_adj = v_float.copy()
15     v_adj[r1] = np.clip(v_float[r1] * (1.0 + 0.3 * mu[r1]), 0, 255)
16     v_adj[r2] = np.clip(v_float[r2] * (1.0 + 0.1 * mu[r2]), 0, 255)
17     v_adj[r3] = np.clip(
18         v_float[r3] * (1.0 - 0.1 * (1 - mu[r3])), 0, 255)
19     v_eq = cv2.equalizeHist(v_adj.astype(np.uint8))
20     return cv2.cvtColor(cv2.merge([h, s, v_eq]),
21                        cv2.COLOR_HSV2BGR)

```

II.13 Intuitionistic Fuzzy Histogram Equalization (IFHE)

```

1  def apply_ifhe(image):
2      hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3      h, s, v = cv2.split(hsv)
4      v_float = v.astype(np.float32)

```

```

5 mean_val = np.mean(v_float)
6 mu      = 1.0 / (1.0 + np.exp(-0.04 * (v_float - mean_val)))
7 nu      = 0.5 * (1.0 - mu)
8 score   = mu - nu
9 score_n = ((score - score.min())
10           / (score.max() - score.min() + 1e-6))
11 v_ifhe  = (score_n * 255).astype(np.uint8)
12 v_eq    = cv2.equalizeHist(v_ifhe)
13 return cv2.cvtColor(cv2.merge([h, s, v_eq]),
14                   cv2.COLOR_HSV2BGR)

```

II.14 Interval Type-2 Fuzzy Histogram Equalization (T2FHE)

```

1 def apply_t2fhe(image):
2     hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
3     h, s, v = cv2.split(hsv)
4     v_float = v.astype(np.float32)
5     mean_val = np.mean(v_float)
6     std_val = np.std(v_float)
7     k = 0.04
8     mu_upper = 1.0 / (1.0 + np.exp(
9         -k * (v_float - (mean_val - 0.5 * std_val))))
10    mu_lower = 1.0 / (1.0 + np.exp(
11        -k * (v_float - (mean_val + 0.5 * std_val))))
12    mu_centroid = (mu_upper + mu_lower) / 2.0
13    v_t2 = (mu_centroid * 255).astype(np.uint8)
14    v_eq = cv2.equalizeHist(v_t2)
15    return cv2.cvtColor(cv2.merge([h, s, v_eq]),
16                      cv2.COLOR_HSV2BGR)

```

II.15 UIQM Metric

PSNR and SSIM are computed using standard functions from the `scikit-image` library. UIQM is implemented from scratch following Panetta et al. [32]:

```

1 def uicm(image):
2     b, g, r = cv2.split(image.astype(np.float32))
3     rg = r - g
4     yb = 0.5 * (r + g) - b
5     return np.sqrt(np.var(rg) + np.var(yb))
6
7 def uism(image):
8     gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
9     sobelx = cv2.Sobel(gray, cv2.CV_64F, 1, 0)
10    sobely = cv2.Sobel(gray, cv2.CV_64F, 0, 1)
11    return np.mean(np.sqrt(sobelx**2 + sobely**2))
12

```

```
13 def uiconm(image):  
14     gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)  
15     return np.std(gray)  
16  
17 def compute_uism(image):  
18     return (0.0282 * uicm(image)  
19           + 0.2953 * uism(image)  
20           + 3.5753 * uiconm(image))
```

Priyanshu Jain

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