FUZZY METHOD FOR UNDERWATER IMAGE ENHANCEMENT

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by

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I, **Vivek Samad (23/CSE/18)**, hereby certify that the work which is being presented in the major project report II entitled "**Fuzzy Method For Underwater Image Enhancement**" in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the **Department of Computer Science and Engineering**, Delhi Technological University is an authentic record of my own work carried out during the period from **August 2023** to **May 2025** under the supervision of **Dr. Kavinder Singh.**

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This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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I hereby certify that the Project titled "**Fuzzy Method For Underwater Image Enhancement**", submitted by **Vivek Samad**, Roll No. 23/CSE/18, Department of Computer Science & Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of **Master of Technology** (M.Tech) in Computer Science and Engineering is a genuine record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in par or full for any Degree to this University or elsewhere.

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FUZZY METHOD FOR UNDERWATER IMAGE ENHANCEMENT

VIVEK SAMAD

ABSTRACT

Enhancing images is a fundamental step for most computer vision and other machine learning tasks, ensuring they are ready for subsequent processing. Underwater image enhancement plays a vital role in improving the visual quality of images affected by low light, color distortion, and scattering effects. Underwater haze and images taken in murky underwater environments often exhibit low visibility and poor contrast and complicates the process of retrieving meaningful details from images, often leading to poor image quality. Improving these images by removing haze not only enhances their clarity but also facilitates further analysis. As a result, haze removal is considered both an essential and demanding aspect of underwater image processing. Therefore, enhancing these images is essential for effective analysis during underwater exploration and inspection tasks. Moreover, to be practical for real-time applications, the enhancement methods must be computationally efficient.

Histogram Equalization (HE) [1] is the most simple and widely used image enhancing method that enhances the contrast of an image by distributing its pixel intensity values. However it overenhances the image and degrades the quality of the image. Under such premises, my current work focuses on the downside of histogram equalization and closely examines the existing contrast enhancement methodolgies. In this project I explore different existing methods and try to incorporate techniques like Fuzzy logic and Discrete Cosine Transform and see how these algorithms increase the contrast of the Underwater images while also preserving the natural look of the image [19][20].

Keywords – contrast enhancement, histogram equalization, underwater image enhancement, fuzzy logic.

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List of Abbreviations, Symbols, and Nomenclature

HE	Histogram Equalization
CLAHE	Contrast-Limited Adaptive Histogram Equalization
AHE	Adaptive Histogram Equalization
BHE	Bi-Histogram Equalization
BBHE	Brightness Preserving Bi-Histogram Equalization
DSIHE	Dualistic Sub-Image Histogram Equalization
FCF	Fuzzy Contrast Factor
FDH	Fuzzy Dissimilarity Histogram
PDF	Probability Distribution Function
CDF	Cumulative Distribution Function
DCT	Discrete Cosine Transform

CHAPTER 1 : INTRODUCTION

1.1 Overview

Underwater image enhancement is crucial due to the significant role visual information plays in marine research, inspection, and autonomous navigation. In computer vision and machine learning applications involving underwater imagery, enhancement is often the initial step to ensure the data is suitable for further analysis. A primary challenge in underwater imaging is poor contrast, which severely impacts the visibility and perception of details.

Human vision is more sensitive to contrast between adjacent pixels than to overall brightness, making low-contrast underwater images especially problematic. Despite advances in imaging equipment, underwater images often remain suboptimal due to factors such as light absorption, scattering, and limitations in equipment or operational expertise. Since many automated systems depend on high-quality visual input, enhancing underwater images prior to analysis is essential for achieving accurate and reliable results. In this context, contrast enhancement aims to highlight important visual features, making them more distinguishable and interpretable.

1.2 Motivation

Histogram-based algorithms [1] enhance image contrast by adjusting pixel intensities according to their histogram distribution. However, these methods often suffer from over-enhancement or under-enhancement due to the dominance or insignificance of certain intensity components. While some techniques attempt to suppress dominant regions and emphasize weaker ones, such manipulations may distort the natural appearance of the image and degrade its visual quality.

Additionally, most conventional algorithms apply transformations solely based on pixel intensity values without considering spatial context. As a result, pixels with the same intensity are uniformly mapped, regardless of their surrounding structures. This can lead to visually unappealing outputs and inadequate enhancement across various image regions.

These limitations include:

- **Over-amplification** of dominant intensity levels and suppression of rare intensities.
- **Loss of contextual integrity**, as pixels are processed without spatial awareness.
- **Uneven contrast enhancement**, where some regions are exaggerated while others remain unaffected, potentially introducing artifacts like checkerboard patterns.
- **High computational cost**, making many algorithms unsuitable for real-time or embedded applications.

These challenges motivate the need for context-aware and computationally efficient enhancement methods that adapt to local image characteristics without compromising overall quality.

1.3 Problem Formulation

Enhancing underwater images poses distinct challenges that go beyond the limitations of conventional contrast enhancement techniques. General-purpose algorithms often fail to adapt to the optical complexities of underwater scenes, which are affected by wavelength-dependent light absorption, scattering, and non-uniform illumination. The following key issues outline the primary obstacles in underwater image enhancement:

A. Non-Uniform Attenuation and Color CastUnderwater environments exhibit wavelength-specific light absorption, resulting in dominant blue-green color casts and inconsistent contrast. Traditional global methods, such as Histogram Equalization (HE) or Brightness Preserving Bi-Histogram Equalization (BBHE), tend to overstretch specific color channels, worsening color distortion and obscuring detail in turbid or low-light areas.

B. Loss of Texture in Smooth RegionsSuspended particles in water introduce multiplicative noise, particularly in smooth or hazy regions. Local enhancement methods may amplify this noise while failing to adequately enhance textures in detailed regions, such as coral structures or marine life.

C. Lack of Context-Aware ProcessingConventional enhancement methods typically apply uniform transformations without considering spatial context. For instance, the same intensity adjustment is applied to both turbid and clear regions, leading to visually inconsistent outputs such as oversaturated foregrounds or inadequately enhanced distant areas.

D. Computational InefficiencyAdvanced techniques like 2D histogram-based methods (e.g., SECEDCT) or iterative approaches (e.g., NDFE) are computationally intensive, rendering them unsuitable for real-time applications in underwater robotics or remotely operated vehicles (ROVs).

E. Sensitivity to Environmental ParametersMany algorithms depend on manually tuned parameters such as gamma values or Retinex scales. However, underwater conditions vary significantly with depth, turbidity, and ambient lighting, necessitating adaptive or parameter-free methods.

F. Inadequate Preservation of Natural AppearanceSeveral enhancement methods introduce artifacts or distort color fidelity, which undermines the authenticity of enhanced images. This is particularly problematic for applications like ecological monitoring, where accurate color representation is critical.

These limitations emphasize the need for a robust, adaptive, and computationally efficient framework that can enhance underwater images while preserving structural details and natural color characteristics.

1.4 Objective

The objective of this work is to develop a contrast enhancement technique for underwater images that leverages contextual information to produce visually balanced and natural-looking results. The proposed method aims to adaptively enhance both grayscale and color images by integrating global contrast adjustment with local detail preservation. This dual approach addresses the limitations of existing methods, such as over-enhancement, artifact introduction, and loss of structural or chromatic fidelity.

1.5 BACKGROUND

1.5.1 Histogram

Histogram-based techniques are among the most commonly used methods for image enhancement due to their simplicity, effectiveness, and low computational cost [1]. These methods improve the visibility of image details by redistributing pixel intensity values, making them especially effective in dark or low-contrast environments such as underwater scenes.

One of the key strengths of histogram-based methods is their scene-independence—they do not require prior knowledge of image content. However, they also have notable limitations. Most traditional approaches apply global adjustments uniformly across the image, without considering local variations. This can lead to over-brightening in certain areas while others remain under-enhanced. Additionally, dominant intensity regions may become exaggerated, and fine details may be suppressed. The lack of contextual awareness often results in visually unrealistic outputs and perceptual artifacts.

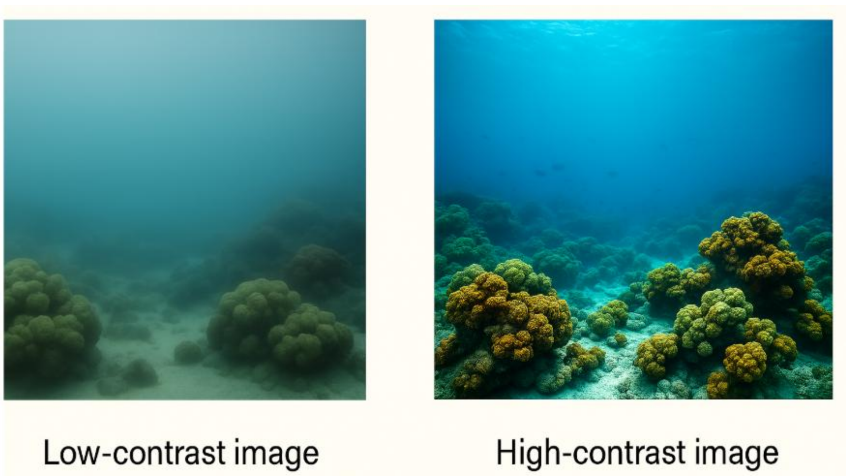


Figure 1: A Low and High contrast Underwater Image

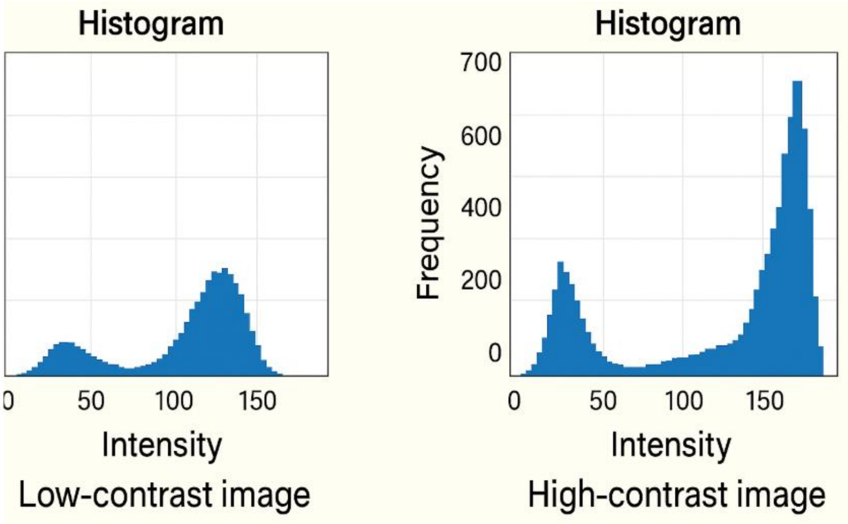


Figure 2: Histogram of the Low and High contrast Image

1.5.2 Histogram Equalization

Histogram Equalization (HE) [1] is a widely used image enhancement technique that improves image contrast by redistributing the intensity values of pixels. The primary goal of HE is to produce a uniform histogram, where all intensity levels occur with roughly equal frequency, thereby enhancing the visibility of features across the image.

The method works by computing the cumulative distribution function (CDF) of the pixel intensity values in the original image and using it as a mapping function to adjust the pixel values. This transformation spreads out the most frequent intensity values, which often results in an image with improved global contrast.

1.5.3 Color Models

A color model, or color space, is a mathematical representation used to describe colors through a set of coordinate values. Each point in the model corresponds to a specific color. Common color models include RGB, CMY, CMYK, and HSI, each serving different purposes depending on the application.

Hardware-oriented models like RGB (used in monitors) and CMYK (used in printers) are based on the additive and subtractive color principles, respectively. In contrast, perceptual models such as HSI (Hue, Saturation, Intensity) better align with how humans interpret color. The HSI model separates chromatic information (hue and saturation) from intensity (brightness), making it especially useful for image enhancement tasks. This separation allows intensity-based operations, like contrast adjustment, to be performed without altering the color content—an advantage for underwater image processing where preserving natural appearance is important.

While numerous color models exist in the field of color science, this work focuses primarily on RGB and HSI due to their relevance in underwater image enhancement.

1.5.4 Fuzzy Logic

Fuzzy logic is a method of reasoning that mimics how humans think and make decisions in real life. Unlike traditional logic (called binary logic) where something must be either true or false (1 or 0), fuzzy logic allows for more flexible thinking where things can be partially true or partially false. It handles the concept of degrees of truth rather than just absolute true/false decisions.

Components of Fuzzy Logic:

A. **Fuzzy Sets**: In fuzzy logic, instead of saying something belongs entirely to one set or another, we say it belongs to a set to a certain degree. For example, a temperature of 25°C might be 0.6 "warm" and 0.4 "cool".
B. **Membership Functions**: These functions define how much something belongs to a particular set. For example, a person’s height can belong 0.7 to the "tall" set and 0.3 to the "short" set.
C. **Fuzzy Rules**: These are "if-then" rules that guide decisions. For example, a fuzzy rule could be: "If the room is somewhat hot, turn the fan speed to medium." These rules are used to manage uncertainty and partial truths.
D. **Defuzzification**: After making a fuzzy decision, the final step is to convert the fuzzy result back to a clear, actionable outcome. For instance, if the temperature is 0.6 "hot," the air conditioner might be set to 60% of its maximum power.

Fuzzy logic is used in many real-world systems, such as washing machines (to adjust wash cycles based on dirtiness), thermostats (to adjust temperature), image processing tasks and even in cars (for controlling things like ABS brakes or cruise control).

1.5.5 Discrete Cosine Transform

The Discrete Cosine Transform (DCT) is a mathematical technique that transforms a signal or image from the spatial domain to the frequency domain. It represents the data as a sum of cosine functions oscillating at different frequencies.

In digital image processing, the DCT is commonly used because it efficiently concentrates most of the signal's energy in a few low-frequency components, making it suitable for tasks like image compression and enhancement. The low-frequency components contain the overall structure or smooth variations of the image whereas the High-Frequency Components represent fine details, edges, and noise.

Hence by manipulating the frequency components, specific characteristics of the image (e.g., contrast, sharpness) can be enhanced or suppressed.

CHAPTER 2 : RELATED WORK

2.1 Literature Survey

Image enhancement techniques generally focus on the visual enhancement through feature manipulations of the images so that they become more suitable for a specified application or are pleasing to human observation. Enhancement techniques can then further be divided into spatial domain and frequency domain methods. Spatially, we directly manipulate the image's pixels. On the other hand, in the frequency domain, manipulations are carried out with the image being transformed into the frequency domain first. Here we look at different existing methods as to how we can improve the contrast of the image.

HE: HE [1] is a contrast enhancement technique that seeks to improve the look and feel of an image through the adjustment of the pixel intensity distribution. This entails the redistribution of pixel intensity values to span the whole range of possible values- say, 0 to 255 for an 8-bit image-so that the resulting image becomes clearer and its details, which might have remained unnoticed due to poor contrast, are improved. While this increases the contrast of features within images, it may tend to give rise to undesirable effects in certain areas, where uniform brightness is already a property.

Sub-Histogram Equalization: Sub-HE [22] is one of the variants of HE, which is a technique used in image processing to enhance the contrast of an image. Generally speaking, histogram equalization tries to adjust the intensity distribution of an image such that the resulting histogram is as uniform as possible, making the details in the image more visible. Sub-histogram equalization decomposes the intensity histogram of the image into several sub-histograms and then equalizes each sub-histogram separately.

First, divide the intensity values of an image into a number of non-overlapping sub-ranges or sub-histograms. The sub-histograms may be defined for fixed ranges of intensity or adaptively obtained according to the nature of distribution of pixel values. Next, equalize each sub-histogram independently: traditionally, the intra sub-range of intensities' contrast is adjusted using histogram equalization. Hence, with this methodology, the local details at distinct regions within the image could be enhanced by operating on independent subhistograms.

CLAHE: CLAHE is an image enhancement methodology developed to enhance contrast perception and thus aid in viewing visual data under a number of conditions. The classical methods, HE and AHE, were improved to overcome potential shortcomings-amplification of noise and over-enhancement that may occur in portions of the image. To avoid over-amplification of noise, CLAHE limits the amount of contrast enhancement. Specifically, the algorithm limits the slope of the CDF in each local region. It does this by setting a threshold on the amount of contrast amplification, known as the "clip limit". If a given pixel intensity exceeds the threshold, it overflows into the other intensity bins in such a manner that the excess gets distributed, thus limiting contrast in areas where it otherwise gets too strong. Then CLAHE performs a histogram equalization for each of the individual tiles and afterward makes use of bilinear interpolation between neighboring regions to avoid possible boundary artifacts. This will ensure smooth transitions between different tiles and thus give an overall natural appearance of the image.

BHE : In this method, the histogram of the image is divided into two subhistograms according to the mean intensity. Each of them is histogram equalized independently. The result avoids too much enhancement in contrast and conserves brightness; however, it sometimes allows insufficient enhancement in contrast for highly dynamic images.

BBHE [7]: This is a variant of BHE in which there is an attempt to preserve image brightness while enhancing the contrast. This version will take into consideration the mean brightness preservation by intelligently redistributing the intensities within both sub-histograms. Maintains overall image brightness and prevents over-saturation but does not perform well on those images where high contrast adjustment is needed.

DSIHE [8]: It is similar to BBHE [7], but it uses the median instead of the mean for splitting the histogram into two parts. Equalization is applied separately to each sub-histogram. It has better contrast enhancement and brightness preservation than BBHE [7], but may not perform well on images with uneven intensity distribution.

Recently, there have been notable breakthroughs in the domain of deep learning for the classification of leaf diseases in apple orchards. Several studies have concentrated on creating novel methodologies and frameworks to enhance the precision of disease diagnosis, the computational effectiveness, and model robustness.

In their approach first [2], Anil et al. introduced the FCCE method with a FSI and a FCF and introduced a novel histogram they call the FDH. The output of FDH is normalized values that in turn are used to build a cumulative distribution function which acts as a transfer function to get the contrast-enhanced image.

Based on the approach proposed by Ashish et al. [5], a new contrast enhancement method combines fuzzy clustering with sub-histograms obtained through discrete cosine transform and is known as Fuzzy Clustering-Based Histogram Model. The image's particular features are maintained by dividing the histogram into sections and each area is equalized individually.

In their work, Reman et al. [4] use fuzzy c-means clustering to enrich the details in an image that are hard for the eye to notice and still preserve the natural look of the picture. In this approach, every pixel is assigned to a group and each pixel gets a membership measurement. Spatial intensity levels are set based on the membership values from the field.

Kankanala et al. [3] proposes a new method for bin stretching in histograms that enhances contrast by making the range of gray levels larger and making gray levels more unpredictable. It combines info from the image's map with DCT [21] to process the picture subject. Global image enhancement comes from context-driven histogram stretching and local features are made sharper due to DCT processing.

Shaad Fazal et al. [9] presents a new technique called Bi-Histogram Equalization with Fuzzy Plateau Limit (BHEFPL), built explicitly to improve underwater images. Our approach which continues from bi-histogram equalization with clipping, uses fuzzy logic to boost the quality of the image, providing more effective results to the viewer. Both numerical results and visual comparisons confirm that this contrast enhancement method does better than several others.

Raju Patel and his colleagues [10] introduce and assess a technique to remove haze and improve colors in underwater images using a multi-image fusion method guided by fuzzy logic. Using the proposed method, the input image is first parallel-processed using CLAHE to handle both color correction and contrast which creates two different images to further explore. These images are then analyzed to generate weight maps based on luminance, chromatic features, and saliency. Finally, six resulting components are fused using Gaussian and Laplacian pyramid techniques, leading to a visually enhanced, haze-free underwater image.

These works collectively demonstrate the dynamic and rapidly changing nature of image enhancement and application of fuzzy logic in image enhancement.

2.1 Datasets

Datasets are essential in digital image processing and underwater image enhancement and typically yield superior accuracy and performance when high-quality data is availabe. A brief discussion of several regularly used datasets for underwater image enhancement is provided and listed in Table 1.

Table 1 - Datasets Used in Underwater Image Enhancement

Dataset Name	Year of Release	Number of Images / Pairs	Description / Notes
UIEB	2019	950 images (890 paired, 60 challenging)	Real-world images, benchmark for enhancement [11].
LSUI	2024	5,004 image pairs	Large-scale, diverse scenes and references [12].
EUVP	2020	Paired: ~24,840; Unpaired: 6,665	Paired and unpaired, various sources [13].
RUIE	2019	Not specified (large-scale, 3 subsets)	Real-world, designed for visibility, color, detection [14].
SQUID	2021	57 stereo pairs (114 images)	Stereo, for color restoration and quantitative eval [15].
U45	2019	45 images	Public test set, diverse degradations [16].
OceanDark	2025	183 images	Low-light images, deep Pacific locations [17].
SUIM	2020	1,525 annotated images (train/val), 110 test	For segmentation, also used in enhancement [18].

CHAPTER 3 : PROPOSED METHODOLOGY

In this work, the HSV color model is used to represent the color images. To enhance contrast effectively, the algorithm focuses specifically on the V (Value) component, which captures the image's brightness or luminance. Since this component contains the non-chromatic details, applying enhancement solely to the V channel allows for improved visibility without altering the color content. The H (Hue) and S (Saturation) components remain unchanged throughout the process, which helps maintain the original color fidelity and prevents distortion of the image's chromatic information.

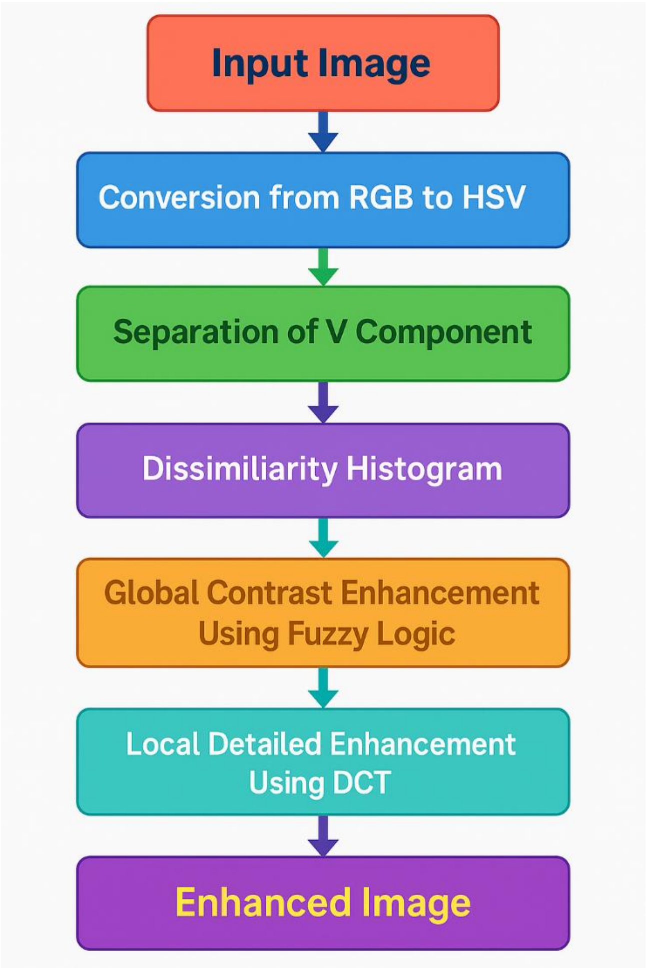


Figure 2 : The framework of proposed algorithm for image enhancement

3.1 Global Contrast Enhancement Using Fuzzy Logic

Here we try to enhance the global contrast of the image by using HE. The fuzzy logic is incorporated into this method[1] so that we can get the contextual information of the pixel with respect to its surrounding

A. Fuzzy Neighborhood Similarity: This is the Fuzzy membership function that calculates the fuzzy similarity of a pixel at position (x, y) to its neighboring pixel at position (u, v). The equation is given as:

$$\mu_{ns}(u, v) = \max\left\{1 - \frac{abs\ (f(x,y) - f(u,v))}{\sigma},\ 0\right\} \tag{3.1}$$

Here f(x,y) is the intensity of the pixel at (x,y), f(u,v) is the intensity of the neighboring pixel at (u, v) and σ(sigma) is the standard deviation of pixel intensities in the image acting as a scaling factor. This equation states that when the difference is small (the pixels are similar), fuzzy similarity is closer to 1. If the difference is large, fuzzy similarity is closer to 0.

B. Fuzzy Similarity Index: This metric measures how similar a pixel is to its neighboring pixels in terms of intensity or color. Here we calculate the fuzzy similarity index (ϕ(x,y)) for the pixel at (x,y) by averaging its similarity values across a 3x3 neighborhood.

A high value indicates that the pixel is similar to most of its neighbors, likely belonging to a smooth area. A low value indicates greater dissimilarity, suggesting that the pixel is in a high-contrast or detailed region.

C. Fuzzy Contrast Factor (FCF): Here we define the fuzzy contrast factor, which measures the dissimilarity of the pixel at (x,y) from its neighbors.

By taking 1−ϕ(x,y) we shift the measure from similarity to dissimilarity. If a pixel has a high similarity index (ϕ(x,y)), it will have a low contrast factor, meaning it is similar to its neighborhood. Conversely, a pixel with a low similarity index will have a high contrast factor, indicating it is in a more detailed or high-contrast region.

D. Fuzzy Dissimilarity Histogram: Once the Fuzzy Contrast Factor has been computed for each pixel, we can use it to construct the FDH. The following equation introduces the FDH which is a collection of values given as

$$H_{fd} = \{ h_{fd}(r_k) \mid 0 \leq r_k \leq L - 1 \} \tag{3.2}$$

L is the total number of intensity levels in the image (e.g., for an 8-bit grayscale image, L = 256, so rk ranges from 0 to 255). Each bin in the FDH measures the accumulated dissimilarity (contrast) for all pixels with intensity rk. Higher values in the FDH bins represent intensities that are more dissimilar (higher contrast) across the image, indicating areas where contrast enhancement is needed.

The following equation calculates the value of FDH bin for each intensity level rk by summing up the values of contrast contribution of a pixel at (x,y) across all pixels in the image.

$$h_{fd}(r_k) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \mu_{r_k}(x, y) \tag{3.3}$$

This computes the FDH bin for each Intensity level which is then used in eq.(9). The sum aggregates the contrast factor values for all pixels with intensity rk, capturing how dissimilar or high-contrast pixels of intensity rk are relative to their neighborhoods.

Now the following equation defines the contrast contribution of a pixel at (x,y) to the FDH bin for intensity rk as:

If the pixel at (x, y) has an intensity equal to rk, then this means that the pixel's contrast factor contributes to the FDH bin, otherwise it does not contribute to this bin. This ensures that each FDH bin only accumulates contrast factors from pixels with intensity rk, creating a histogram that reflects contrast variations at each intensity level.

E. Probability Distribution Function(PDF): Once the FDH is constructed, it provides a histogram that reflects how dissimilar or high-contrast each intensity level is across the image. The next step is to use this histogram to redistribute intensity levels in a way that enhances the contrast, especially in areas with high local differences (dissimilarity). The following equation normalizes the FDH bin for each intensity level rk to create a probability distribution.

$$p_{fd}(r_k) = \frac{h_{fd}(r_k)}{\sum_{k=0}^{L-1} h_{fd}(r_k)} \qquad (3.4)$$

The denominator is the sum of all FDH values across all intensity levels, which normalizes the histogram so that the values PDF sum to 1.

The result PDF is a probability-like distribution, showing the proportion of dissimilarity associated with each intensity level in the image. This normalized distribution will be used to create a cumulative distribution function in the next step.

F. Cumulative Distribution Function(CDF): The following equation calculates the CDF by summing the normalized values of PDF from intensity 0 up to rk.

$$C_{fd}(r_k) = \sum_{j=0}^{k} p_{fd}(r_j) \qquad (3.5)$$

The CDF serves as a transformation function that maps the original intensities in the image to new, enhanced intensity values. As the CDF increases, it distributes intensity levels across the available range, enhancing contrast in areas where the FDH values are higher.

G. Intensity Transformation: The following equation maps the original intensity rk to a new enhanced intensity sk based on the CDF.

$$s_k = s_0 + (s_{L-1} - s_0) \times C_{fd}(r_k) \qquad (3.6)$$

This transformation adjusts each intensity based on its cumulative contrast (dissimilarity) in the image. Pixels with intensities corresponding to high FDH values (indicating high contrast) will have larger CDF values and be mapped to more spread-out intensities, enhancing their contrast. Conversely, smooth areas with low FDH values will have smaller CDF changes, preserving their natural smoothness.

3.2 Local Detail Enhancement with DCT

A. 2D Discrete Cosine Transform (DCT): In this part of the proposed method, Discrete Cosine Transform (DCT) is used to enhance the local details of the globally enhanced image obtained from the previous step[2]. DCT operates in the frequency domain, breaking down the image into different frequency components. The goal here is to fine-tune the local contrast while maintaining the global enhancements, ensuring that the final image retains rich details.

$$DCT_{pq}(p,q) = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I_g(x,y) \cos\left(\frac{\pi(2m+1)p}{2M}\right) \cos\left(\frac{\pi(2m+1)p}{2M}\right) \quad (3.7)$$

where,

Ig(x,y) represents Pixel intensity from the globally enhanced image.

M and N are dimensions of the image block (e.g., 8×8).

p and q are frequency indices (low or high frequencies).

αp and αq are scaling constants.

The DCT converts the pixel intensities of the image from the spatial domain to the frequency domain, where Low frequencies represent smooth variations in intensity (e.g., background) and high frequencies capture finer details (e.g., edges and textures). Scaling Constants (αp and αq): These scaling factors ensure energy conservation in the DCT. The coefficients are adjusted depending on whether they correspond to the DC component (p,q=0) or other frequencies.

B. Adaptive Tuning of DCT Coefficients: This step fine-tunes the frequency coefficients high-magnitude coefficients (representing significant details) are preserved and low-magnitude coefficients (representing noise or minor variations) are adaptively scaled by a factor β.

Adaptive Scaling Factor (β): Computes the scaling factor β for adjusting low-magnitude DCT coefficients. It depends on the difference in standard deviation (SD) between the enhanced image (Ig) and the input image (I).

$$\beta = 1 + \left|\frac{SD(I_g) - SD(I)}{255}\right| \tag{3.8}$$

where,

SD(Ig): Standard deviation of the globally enhanced image.

SD(I): Standard deviation of the original image.

β: Determines the level of local enhancement

CHAPTER 4 : RESULTS AND ANALYSIS

The proposed algorithm has been evaluated across a wide range of low-contrast images to ensure its robustness. The datasets used for testing include the UIEB (Underwater Image Enhancement Benchmark Dataset) and LSUI (Large-Scale Underwater Image Dataset). To assess its effectiveness, the method was applied to over 500 images, and its performance was analyzed through both quantitative metrics and visual comparisons.

4.1 Quantitative Assessment

With so many visual quality differences from one image to another, it's often hard to accurately compare how effective contrast enhancement algorithms are by using numbers. Different techniques tend to fall short under certain conditions. Since many enhancement algorithms focus primarily on the brightness information while preserving color, these contrast evaluations are performed using the luminance component of the image. To assess contrast quality in this work, following metrics are used, each metric serves a specific purpose—some measure contrast improvement, others quantify similarity or naturalness.

A. AMBE (Absolute Mean Brightness Error)

Measures the difference in average brightness between the **original** and the **enhanced** image. A lower AMBE value indicates better brightness preservation.

$$AMBE = |\mu_O - \mu_E| \qquad (4.1)$$

- μo: Mean brightness of the original image
- μE: Mean brightness of the enhanced image

Example: A smaller AMBE value (closer to 0) is better.

B. PSNR (Peak Signal-to-Noise Ratio)

Measures the **quality** of the enhanced image compared to the original. Higher PSNR indicates the enhanced image is more similar to the original (less distortion).

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \qquad (4.2)$$

- MAXI: Maximum possible pixel value (255 for 8-bit images)
- MSE: Mean Squared Error between original I and enhanced K:

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}[I(i,j) - K(i,j)]^2 \qquad (4.3)$$

Example: A **PSNR > 30 dB** is generally considered good.

C. **SSIM (Structural Similarity Index Measure)**

Evaluates the **structural similarity** between original and enhanced images [6]. Values range from **0 (no similarity)** to **1 (identical)**.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (4.4)$$

- μx, μy : Mean of images xxx and yyy
- σx2, σy2 : Variance
- σxy : Covariance
- C1,C2 : Stabilizing constants

Example. If SSIM = 0.92, the enhanced image is very similar to the original in terms of structure.

D. Entropy

Measures the **amount of information** or **detail** in an image. Higher entropy usually indicates richer texture and better enhancement.

$$Entropy = -\sum_{i=0}^{L-1} p(i) \cdot \log_2 p\,(i) \qquad (4.5)$$

- L : Number of gray levels
- p(i) : Probability of each gray level i

Example: If an image has evenly distributed pixel intensities, entropy will be higher, closer to 8 for 8-bit images. Low entropy may indicate loss of detail or over-smoothing.

E. Standard Deviation (SD)

Indicates the **contrast level** in an image. Higher standard deviation means greater contrast and variability in pixel intensity.

$$SD = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(I(i,j) - \mu)^2} \qquad (4.6)$$

- μ: Mean intensity of the image
- I(i,j) : Pixel intensity at position (i,j)

Example: An image with SD = 25 has more variation in intensity than one with SD = 5.

Table 2 – Comparison of Different Metrices

Metric	Ideal Value	Use Case	Pros	Cons
AMBE	Low (≈0)	Brightness preservation	Simple computation	Ignores spatial information
PSNR	High (>30)	Compression/Reconstruction	Widely used	Poor perceptual correlation
SSIM	High (~1)	Perceptual quality assessment	Human vision-aligned	Computationally intensive
Entropy	Moderate	Texture/complexity analysis	Information-theoretic measure	Doesn't account for structure
Std Dev	Contextual	Contrast/noise evaluation	Easy to interpret	Sensitive to outliers

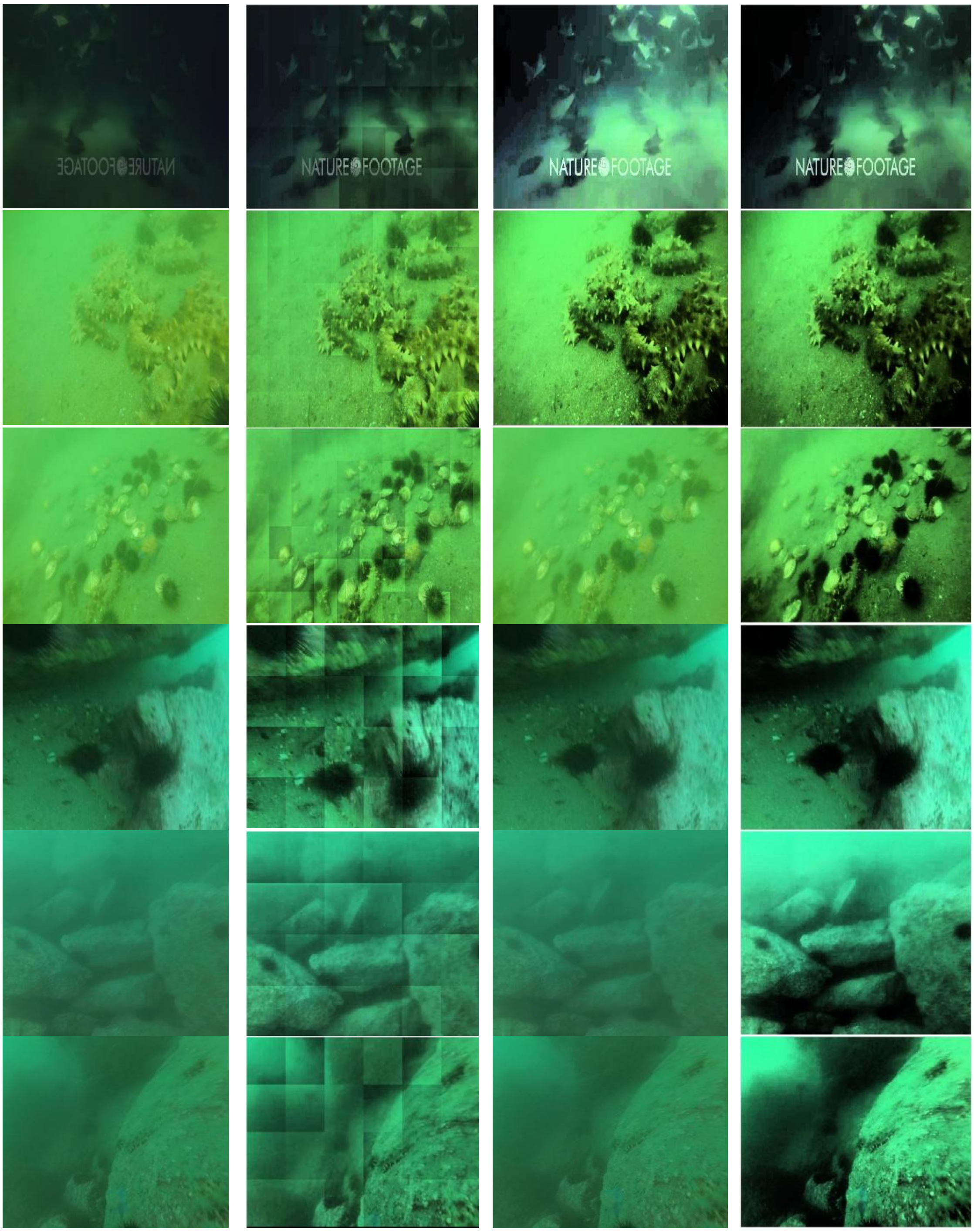
The proposed algorithm is tested on nearly all kinds of low contrast underwater images. The image databases used in this are: UIEB (Underwater Image Dataset) [11], LSUI (Large-Scale Underwater Image Dataset) [12], EUVP (Enhancing Underwater Visual Perception) [13]. The table below shows the output of different metrices on those images.

Table 3 – Output of the Dataset Images on Different Metrices

	AMBE	PSNR	SSIM	Entropy	Std Dev
Image 1	0.1279	12.6441	0.6001	5.3579	24.77
Image 2	0.1113	12.3510	0.6353	6.9479	29.18
Image 4	0.0009	19.0428	0.8214	7.3005	30.06
Image 7	0.0861	15.8217	0.6695	7.8467	28.73
Image 9	0.0496	15.0081	0.6846	7.8094	30.97
Image 10	0.0512	18.8138	0.8465	7.4815	29.79
Image 11	0.0400	16.7397	0.7403	7.8693	30.70
Image 14	0.0715	16.0696	0.7500	7.2504	27.60

4.2 Visual Assessment

Contrast in an image cannot be evaluated solely based on quantitative metrics, as a higher numerical score does not always correspond to better visual quality. For this reason, a visual comparison of the results produced by the enhancement method is also included in this section. Sample output images along with their respective histograms for the algorithm are illustrated in Figures 3 to 8, covering both grayscale and color images for a comprehensive visual analysis.



1 2 3 4

Figure 3: Comparison between 1 Original, 2 Clahe, 3 Stnd. HE and 4 Proposed

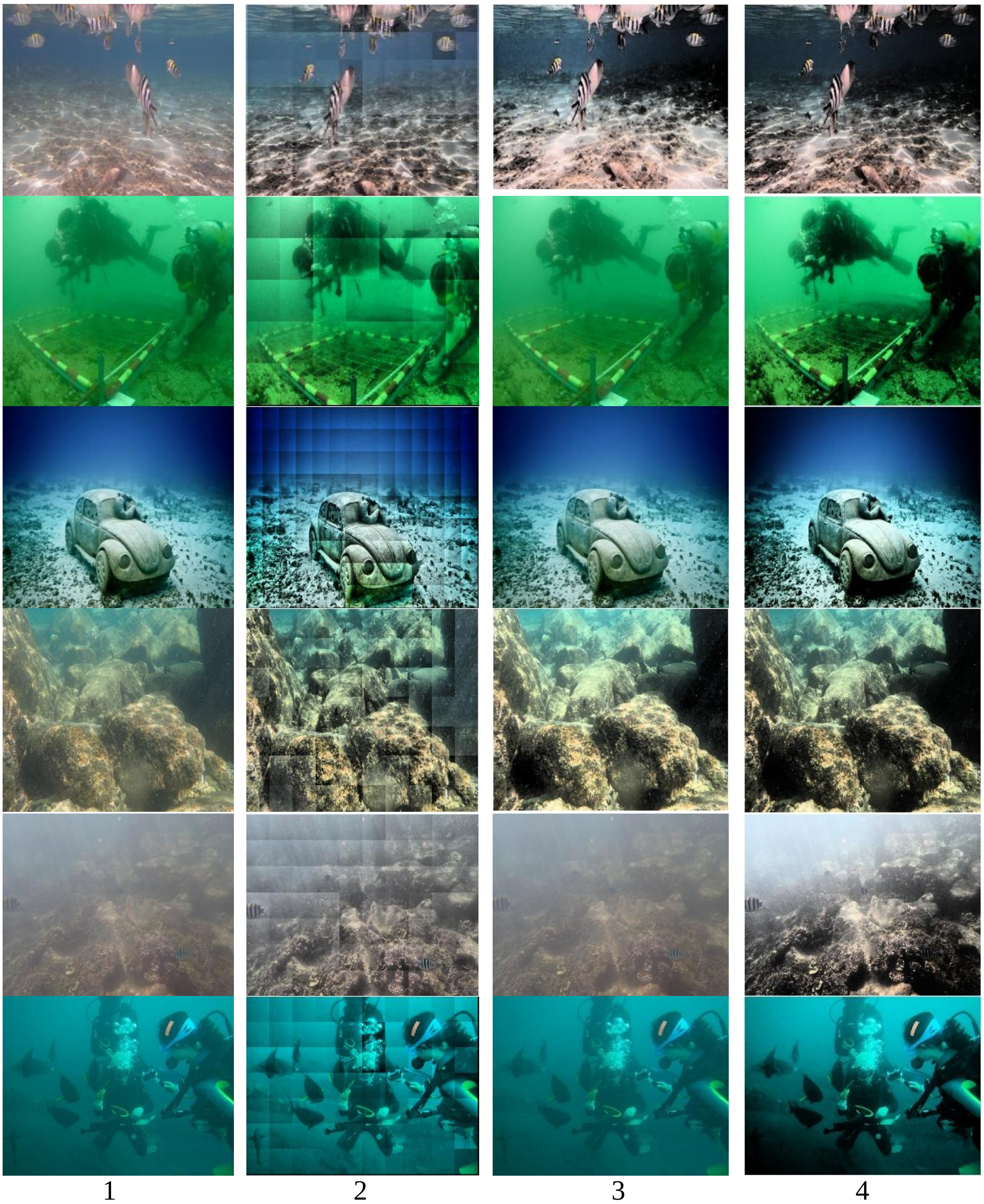


Figure 4: Comparison between 1 Original, 2 Clahe, 3 Stnd. HE and 4 Proposed

CHAPTER 5 : CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This thesis aims to illustrate the significance of underwater image enhancement in managing the main problems in underwater images such as poor illumination and lost or warped colors. Improving contrast in these types of images is significant because it affects the reliability and usefulness of object detection, supportive research in the sea and autonomous vehicles beneath the water. In machine learning and computer vision, making images better quality is often an important first part of the process that greatly improves the accuracy and dependability of algorithms.

Dealing with the uncertainty and imprecision in underwater images has now become easier thanks to fuzzy logic. Thanks to fuzzy logic which imitates real human thought, image enhancement can be more flexible and better suited to changing situations found in underwater locations. All along, we showed that using fuzzy logic on underwater pictures improves their contrast and sharpness and does a better job than typical methods, both visually and by numbers.

This research can be carried further by exploring fuzzy logic together with deep learning models or real-time image enhancements for both underwater robotics and environmental surveillance. Joining all these approaches may result in better, stronger and more efficient ways to image inside water.

5.2 Future Scope

In the future, enhancing underwater images may benefit a lot from new algorithms built using fuzzy logic. Although the present method has improved both contrast and clarity, some of the enhanced images still show faint haze or low sharpness in regions with many fine details. Further studies should concentrate on creating fuzzy systems that adapt their parameters to suit different situations in the ocean such as depth, how clear the water is or the intensity of light.

Integration of fuzzy logic with different methods such as deep learning, multi-scale image fusion or optimization algorithms, might result in new models that benefit from two different types of systems. Such methods can also be applied right away on embedded systems used in underwater drones or autonomous submarines, leading to smarter choices on the spot.

To improve even more, it would be useful to add sonar or depth data to the inputs, alongside optical images, in these systems. If these difficulties are met, future studies can help strengthen solutions for underwater exploration, monitoring and protecting the environment.

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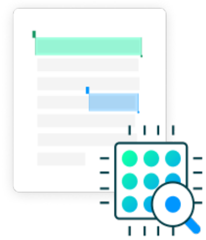

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