INTERNSHIP REPORT

Evaluation of Underwater Image Processing Algorithms

NIHITHA MALAYARUKIL

Masters in Artificial Intelligence

02-05-2024 - 31-10-2024

Tutored by:
Myriam Tami
MICS Lab, CentraleSupelec

Supervised by:
Hai Nam Tran
Lab-STICC, University of Brest
Vincent Rodin
Lab-STICC, University of Brest
Barbara Džaja
Faculty of Science, University of Split

October 21, 2024

Gratitude

First of all, I would like to express my gratitude to Univeristy of Brest, University of Split and Lab-STICC for allowing me to do this internship, which has greatly contributed in development of my skills and knowledge. I would also like to thank CentraleSupelec for the excellent training they provided me.

Particularly, I would like to thank my internship supervisor, Hai Nam Tran, for his exceptional guidance throughout the internship. I would also like to thank Barbara Džaja and Vincent Rodin for giving support and sharing ideas, all of which helped me explore various aspects of my work.

I would also like to express my gratitude to Myriam Tami, my university tutor, for her invaluable support.

Finally, I extend my heartfelt thanks to all the interns, doctoral students, and researchers for their warm welcome and making my internship experience truly memorable.

CentraleSupélec

Ackowledgement

This internship report presents the work carried out in Lab-STICC on the topic of Image Processing. The main objective of this internship is to analyze various image processing techniques for the enhancement of underwater distorted images using Matlab software. This study focussed on developing an empirical method to select the most suitable algorithm for a given distorted input image.

In real-time processing, both execution time and memory consumption are critical factors. With this in mind, I also explored the implementation of a model to automatically select the optimal algorithm for a given image. This approach not only saves the time but also ensures that the most effective method is chosen for enhancing the image.

Contents

Abbreviations

ARC	: Automatic Red-channel restoration
BRISQUE	: Blind/Referenceless Image Spatial Quality Evaluator
DCP	: Dark Channel prior
HE	: Histogram equalization
NORM	: Euclidean distance
NIQE	: Naturalness Image Quality Evaluator
PSNR	: Peak Signal-to-Noise ratio
SCB	: Simplest Color balance
SSIM	: Structural Similarity Index Measure
UICM	: Underwater Image Colorfulness Metric
UISM	: Underwater Image Sharpness Metric
UIConM	: Underwater Image Contrast Metric
UIQM	: Underwater Image Quality Metric
WB	: White Balance
MSR	: Multi Scale Retinex
AutomatedMSR	: Multi Scale Retinex Automated Color restoration

List of Figures

List of Tables

Chapter 1

Introduction

Ocean covers more than 70% of the Earth's surface and holds valuable minerals, rare earth elements, incredible marine life. While some marine creatures are threatened to extinction, valuable mineral deposits also exist beneath the ocean's surface. Therefore, exploring and utilising the ocean's resources requires a balanced approach that includes conservation efforts to protect endangered species. Light is a crucial element for capturing scenes, but in real-time scenarios, adequate lighting is often lacking. Significant improvements in computer vision are being made to enhance underwater images.

Many algorithms have been developed in image processing to improve quality of an image, but they may fail or produce lower-quality results depending on various properties of light. Each algorithm tries to eliminate distortions such as haze, attenuation, and absorption, that affects underwater images quality. However, a universal algorithm for all kinds of distorted images does not exist. There is a need for an empirical approach to find a suitable algorithm for a given distorted input image.

This work is a part of **SEA-EU ROV Operate project** and it is funded by Investissements d'avenir (ANR) in 2020. The project is a collaboration between University of Split (University Department of Professional Studies, and Faculty of Science), and University of Brest (Computer science department/Faculty of Sciences and Lab-STICC). Lab-STICC is a laboratory affliated to CNRS where researchers work on various aspects(from sensors to knowledge). University of Split has designed a ROV (Remotely Operated Underwater Vehicle) for marine infrastructure inspection. The current ROV is manually operated, connected to a ground control station via a wired link for power and communication, and has limited computational capabilities. A new version is being developed by the University of Split to provide sufficient computing resources to support demanding applications like image processing. Integrating such computationally intensive software could enable the ROV to become autonomous, but it is challenging to manage computational resources. Regardless of whether the ROV is autonomous, it must meet strict safety and real-time operational requirements. Therefore, this project works on balancing these constraints with the need to execute resource-intensive tasks, while operating within the confines of limited energy availability. In the ROV-Operate project, the consortium will pursue two main objectives: 1) designing and optimizing the ROV's software architecture, including both control and payload components, using AADL, and 2) implementing and managing underwater image processing and object detection algorithms using the ROV's cameras and computational resources.

1.1 Resources

1.1.1 Database Resources

In this work, Database for underwater images were collected from various sources. They are processed using image processing algorithms. Later, trained and tested on standard neural networks.

- As part of a collaboration with SEA-UE and University of Split in Croatia, a rover intended for underwater research has been purchased. Chasing Dory is a portable and compact underwater drone intended for the general public. By connecting the cable between the drone and the repeater, and using the Chasing Dory mobile application, the drone can be controlled remotely. The drone moves at a speed of up to 1 meter per second. It is equipped with a low-light camera (f/1.6) and can capture images at depths of up to 15 meters. The drone is wired to a floating base - buoy, allowing for precise movements with up to 45 degrees of inclination. It has a 4800 mAh battery and weighs 1.3 kg.

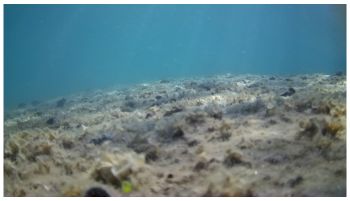
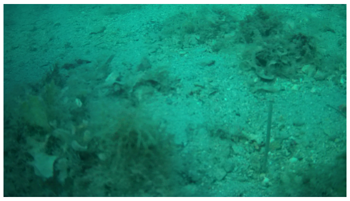

Figure 1.1. *Example images of Chasing Dory*

- Underwater Image Enhancement Benchmark (UIEB) contains 890 images collected from various indoor environments, including information such as Bluetooth beacons and environmental sensors. These underwater images are taken under natural light, artificial light, or a mixture of these lights. Moreover, the corresponding reference images for 890 images are provided following a laborious, time-consuming, and well-designed process. It provides a platform to evaluate the performance of different underwater image enhancement algorithms.


Figure 1.2. *Example images of UIEB Dataset*

- EUVP (Enhancing Underwater Visual Perception) dataset was created to make supervised training of underwater image enhancement algorithms easier. The dataset includes both high-quality and low-quality image samples, as well as paired and unpaired image samples. It contains images from a variety of aquatic environments, including rivers, seas, rocky terrain, seagrass beds, and coral reefs. The features of actual underwater settings are reflected in these images. It is obtained by considering several factors, such as lighting, camera equipment, and water quality. A number of variables, including illumination, camera equipment, and water quality, are taken into account when obtaining the dataset. To capture images in various lighting conditions, they employed HD cameras from Trident ROV, GoPro cameras, low-light USB cameras, and uEye cameras from Aqua AUV. These data include pictures taken from many publicly accessible YouTube movies, from ocean exploration and human-computer collaboration experiments in a variety of settings and with varying visibility. Because of these reasons, the pictures in the EUVP have been carefully chosen to account for the vast range of natural variability and lighting. By controlling these factors, the quality and reliability of the data are ensured, providing an important database for model training.

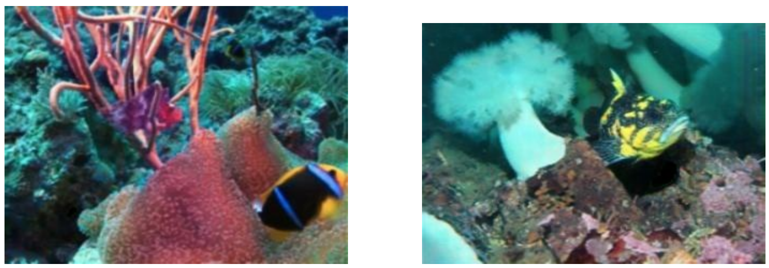

Figure 1.3. *Example images of EUVP Dataset*

1.2 Problem statement

Underwater images captured by ROVs are often subjected to various distortions such as noise, blurring, color degradation, and reduced contrast. These distortions can significantly affect the performance of image processing techniques, which are critical for tasks such as object detection and environmental monitoring. Given the wide range of available image processing algorithms, selecting the most suitable one for a specific distorted image is a challenging task. This selection process is further complicated by the need to balance image quality enhancement with real-time processing and limited computational resources.

The primary challenge is to develop an approach that can automatically select the most appropriate image processing algorithm based on the type and severity of distortions in the image. This involves evaluating the quality of the distorted image using both reference and no-reference quality metrics and implementing a supervised classification model, leveraging standard neural networks, to automate the selection process. The solution must optimize image quality while maintaining real-time performance, making it suitable for deployment in resource-constrained environments like ROVs.

1.3 Objective

The goal of this internship is to develop an approach for selecting the most suitable algorithm for a given distorted image from various image processing techniques, by considering quality metrics (both reference and no-reference metrics). Additionally, the implementation of a supervised classification model using standard neural networks will enable the automatic selection of the most appropriate algorithm.

1.4 Report Outline

This internship report is organised as follows. Chapter 1 gives an introduction to problem statement, objective behind the implementation of underwater image processing algorithms as well as the source to the Dataset.
Then, Chapter 2 introduces the importance of underwater image processing, reviews all related works in the field, and discusses the necessity of neural networks.
Chapter 3 is focused on evaluation of underwater images based on various metrics, Database creation and network implementation.
Finally, Chapter 4 presents the conclusion and outlines future work.

Chapter 2

Background and Related Work

In this chapter, importance of underwater image processing algorithms using Matlab, neural networks is being discussed. These methods are tested on standard database such as UIEB [1], EUVP [2] and Chasing Dory to measure quality metrics of restored images. Along with processing time, memory consumption were also taken into account to understand the algorithm's significance from various perspectives.

2.1 Underwater Image Processing

Underwater image processing refers to a set of techniques and algorithms designed to enhance, analyze, and interpret images captured in underwater environments. These environments present unique challenges, as images taken beneath the water surface are often affected by light absorption, scattering, and color shifts due to various properties of water. These effects result in degraded image quality, with common distortions such as reduced contrast, blurriness, noise, and color imbalance. Underwater image processing methods aims to correct these distortions, enables clearer and more accurate visual data for applications like object detection, environmental monitoring, and marine exploration. By leveraging image enhancement, restoration, and detection algorithms, we can improve the visibility and usefulness of underwater images in both scientific and industrial domains.

Figure 2.1. *Before Processing*

Figure 2.2. *After Processing*

2.1.1 Importance of Image Processing Algorithms in Underwater Applications

Image processing algorithms play a crucial role in underwater applications due to inherent challenges associated with capturing clear and detailed images in such environments. The importance of these algorithms lies in their ability to improve the quality and interpretability of images that are often degraded by water's optical effects. Enhanced images allow better detection and identification of underwater objects, organisms, and geological features, which is crucial for various fields such as marine biology, archaeology, and underwater infrastructure inspection. Furthermore, advanced image processing enables the automation of tasks such as object recognition, tracking, and classification, reducing the need for human intervention and improving the efficiency of underwater operations. In addition, the ability to process and enhance images in real-time can significantly improve the safety and accuracy of remotely operated vehicles (ROVs), autonomous underwater vehicles (AUVs), and other underwater systems. Without effective image processing algorithms, many underwater exploration and monitoring tasks would be significantly hindered by poor image quality.

2.1.2 Matlab Processing

Matlab is a programming software environment widely used for image processing due to built-in functions and tools. Especially in image processing, it provides a flexibility to manipulate, analyze, and enhance images through different techniques such as filtering, segmentation, and feature extraction.

For underwater image processing, Matlab can be used to apply edge-cutting algorithms to address common issues that occur in underwater images. It helps researchers to implement several algorithms to improve quality of image. Matlab also allows real-time visualization, making it easier to test and refine image processing techniques. It can efficiently handle matrix operations using toolboxes such as the Image Processing Toolbox and the Computer Vision Toolbox, making it an ideal choice for developing and testing image enhancement methods to improve underwater visuals.

Figure 2.3. *Example images of EUVP Dataset*

2.2 Related Work

Kaiming in [3] has proposed a method called Dark Channel Prior (DCP) to restore haze free images. But, proposed method was applied on outdoor scenarios. In this work a total of six underwater algorithms from [4] and [5] were taken into consideration to focus on different aspects to restore enhanced image. They are: Automatic Red Channel[6], Fusion [7], Backscattering [8], Hazelines [9], Local color mapping and color transfer [10], Automated Multi Scale Retinex Color Restoration[11].

2.2.1 Automatic Red Channel Restoration (ARC)

As we go deeper into the water, the red intensity decays faster than blue and green channels which results in absorption of specific wavelengths. Considering this fact, Galdran et al.[6] modified transmission map in Dark Channel Prior to Red Channel Prior with an aim to restore missing color channels as in equation (2.1). This equation estimates the depth of the scene and the color of veiling water to obtain an enhanced image.

$$\tilde{t}^R(x) = 1 - \min\left(1 - \frac{\min\limits_{y\in\Omega(x)} I^R(y)}{1-A^R}, \frac{\min\limits_{y\in\Omega(x)} I^G(y)}{A^G}, \frac{\min\limits_{y\in\Omega(x)} I^B(y)}{A^B}\right),$$
$$\tilde{t}^G(x) = (\tilde{t}^R(x))^{\lambda_G},$$
$$\tilde{t}^B(x) = (\tilde{t}^R(x))^{\lambda_B}. \tag{2.1}$$

Where, t(x) is the transmission of light which is not scattered, A is chosen as the least value out of the top 10% of brightest pixels of color channel, y is the pixel location at every local patch $\Omega(x)$, I is the acquired image vallue at each local patch y in color channels R, G, B, and λ_G & λ_B are attenuation coefficients ratios of green and blue channels.

2.2.2 Fusion

Due to attenuation of the light, captured image can have poor scene contrast, Prachi et al.[7] came up with the approach to increase visibility of distant objects affected due to this problem. Input image is equalized using Contrast Limited Adaptive Histogram (CLAHE) and followed by guided filter to improve visual clarity. The general procedure of fusion method is explained in Figure 2.4.

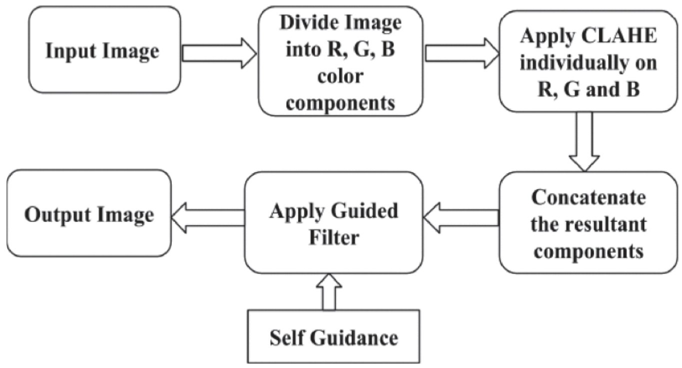

Figure 2.4. *Flow diagram of Enhanced fusion method*

2.2.3 Backscatter Removal

Objects present underwater can cause backscattering, as these objects exhibit reflectance, leading to image distortion. Zhang et al.[8] have solved this issue by seperating input image into illuminance and reflectance components. Individually, these compoenents are corrected using laplacian and gaussian pyramids. Finally, fused using Multi-scale fusion method as shown in Figure 2.5

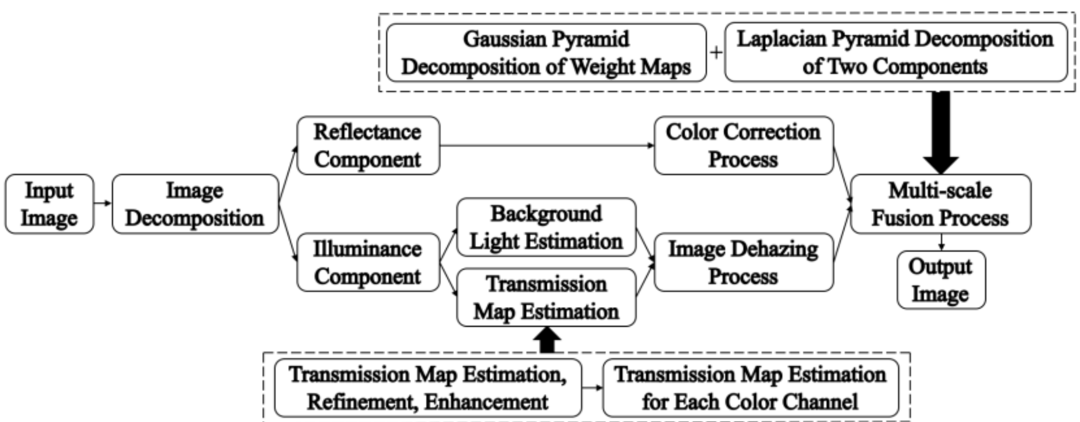

Figure 2.5. *The general procedures of objects visibility enhancement process*

2.2.4 Hazelines

Light attenuation is not constant under water, as water has different attenuation coefficients based on factors such as climatic conditions, seasons, etc. Sathya et al.[12] implemented Dark Channel Pior on underwater images and observed patches of haze-free images. However, haze persits due to attenuation of light caused in different water types. Berman et al.[9] came up with a solution by finding two attenuation ratios such as considering blue-red and blue-green colour channels. Thereby, reducing them to a single image dehazing problem to find transmission map $t_c(x)$ in equation (2.2).

$$I_c(\mathbf{x}) = t_c(\mathbf{x})J_c(\mathbf{x}) + (1 - t_c(\mathbf{x}).A_c, \forall c \in \{R, G, B\} \tag{2.2}$$

Where bold $\mathbf{x}$ is the pixel coordinate, I_c is the observed intensity or acquired image at pixel location x in color channel c, J_c is the scene radiance of the non-degraded image, and A_c is the veiling light found by taking average of pixels largest component of edge map constructed using structured edge detection toolbox (in Matlab).

2.2.5 Local Color Mapping and Color Transform (LCMCT)

When images undergo through global transformation it can lead to over-enhancement or result as an unnatural image. Protasiuk et al.[10] introduced a local color correction method to enhance images. The local color mapping can be achieved with a set of pixels whose underwater color is already known. It computes and matches covariances of input image and reference image to achieve global color transformation as in equation (2.3). A third term is added to resolve saturation of red channel in the image.

$$\min_{A,b} f(A,b) = \underbrace{\| AX - Y + b1_3^T \|_F^2}_{\text{Local Color Mapping}} + \frac{\lambda_1}{2} \underbrace{\| AC_iA^T - C_r \|_F^2}_{\text{global Color Transfer}} + \frac{\lambda_2}{2}(\| A \|_T^2 + \| b \|_2^2) \tag{2.3}$$

Where X & Y are input & reference image, C_r is apriori reference image covariance and λ_1 & λ_2 are the parameters to be adjusted.

2.2.6 Automated Multi Scale Retinex Color Restoration (AutoMSRCR)

Images captured under a wide range of non-linear illumination are distorted. In this context, Petro and Parthasarathy [13] and [11] have introduced their approaches to color restoration methods aimed at maintaining a gray-world assumption (where the average of all color channels is the same). Further, resultant image can be clipped by choosing upper and lower clipping points as in equation (2.4),

$$R_{MSRCRi}(x,y) = G[C_i(x,y)R_{MSRi(x,y)} + b] \tag{2.4}$$

Where, Ci is the color restoration factor to adjust the color proportion of the 3 color channels by applying simplest color balance, G and b are final gain and offset values $b = 30$, $G = 192$, and $R_{\mathrm{MSRi}}(x,y)$ is the weighted average of n single scale images.

2.3 Neural Networks

Neural networks are inspired by the structure of the human brain. It consists of neurons that help process data through weighted connections. They are designed to identify patterns and relationships in given data by learning from labelled examples. Learning helps them make predictions more easily on tasks. Each layer in a neural network performs a mathematical transformation on the input data, passing the results to the next layer and this process continues until the final output is produced. In the training phase, neural networks adjust the weights of the connections based on the errors they make, gradually improving their ability to recognize complex patterns.

2.3.1 Importance of Neural Networks for Image Processing

Neural networks have become essential in the field of image processing due to their ability to effectively analyze, interpret, and classify visual data. Unlike traditional image processing methods they rely on predefined rules or filters but, neural networks can automatically learn to extract meaningful features from images during training process. This capability is particularly valuable when dealing with complex and high-dimensional data such as images. By learning features from low-level ones like edges and progressing to high-level ones like objects and scenes. Neural networks can achieve good levels of accuracy in image based tasks. Additionally, their ability to handle noise, distortion, and variability in image data makes them highly useful in challenging environments like underwater imagery, where distortions such as blurring, noise, and color shifts are common. Neural networks flexibility and accuracy make them important tool for automating and improving the quality of image processing across various applications, from medical imaging to autonomous vehicle navigation.

In this work EfficientNet model [14] is used for training underwater images to select best algorithm for a given image. EfficientNet architecture in Figure 2.6 achieved good performance on various benchmark dataset with few parameters and less computational power than other models such as ResNet or VGG. It is quite popular because of its scaling method in a structural way to maximize performance while minimizing computational cost.

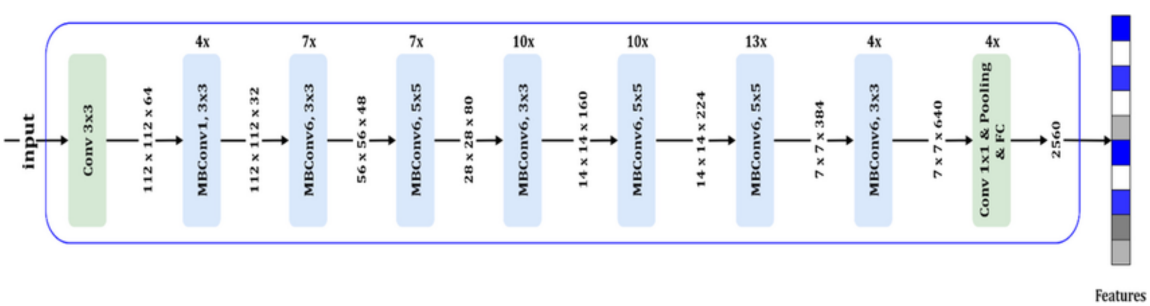

Figure 2.6. *EfficientNet Architecture*

Chapter 3

Contributions

This chapter discusses the creation of a dataset for a suitable underwater image processing algorithm based on quality metrics. Additionally, it presents a fine-tuned neural network capable of classifying the best algorithm for a given input image.

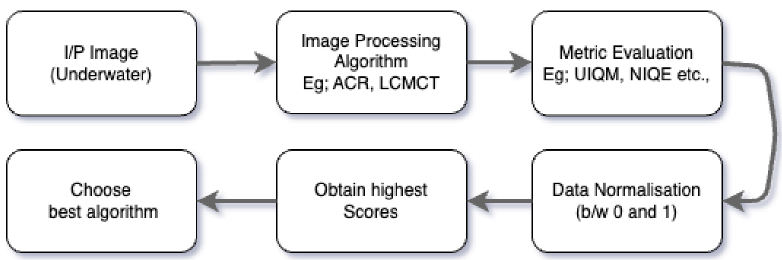

Figure 3.1. *Flow Chart of Database Creation*

3.1 Evaluation of underwater images processing algorithms

It is the second step in our process according to Fig 3.1. In the evaluation of underwater image processing algorithms, Matlab is used to process underwater images. To address various challenges inherent in underwater imaging, six distinct algorithms: ARC, HazeLines, Local Contrast Mapping and Color Transfer (LCMCT), Image Fusion, Backscatter Removal, and AUTOMSRCR are implemented. Each of these algorithm was selected for its ability to tackle specific issues related to image degradation, aiming to enhance the overall quality of the underwater images. Through systematic application and analysis of these techniques, we were able to get image clarity, better interpretation and analysis of underwater scenes. Figure 3.2 is a reference to implementation of each algorithm. Also, Figure 3.3 shows results of above mentioned algorithms in Matlab software.

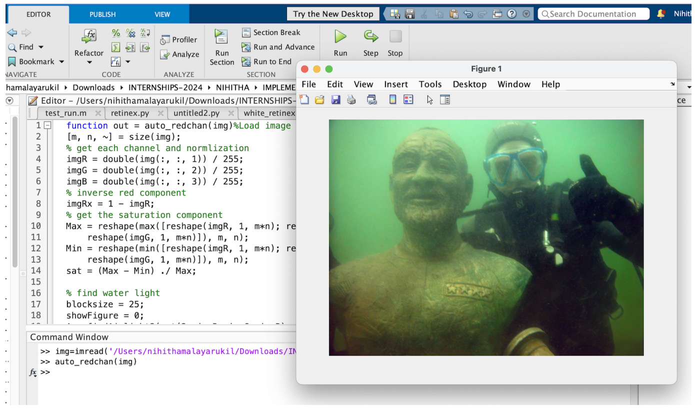

Figure 3.2. *Implementation of ARC Method in Matlab*

3.2 Evaluation Criteria

Evaluation criteria is the third step presented in Figure 3.1. To evaluate quality of an image enhanced by underwater image processing it is important to determine criterias. In this work total of 6 metrics are considered, in which 3 are reference and others are no-reference metrics. They are Underwater Image Quality Measure (UIQM)[15], Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE)[16], Natural Image Quality Evaluator (NIQE)[17], Euclidean Distance (NORM) [18], Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM)[19]. Table 3.1 shows the metric evaluation for all underwater image processing techniques on Figure 2.1

3.2.1 No reference metrics

Underwater Image Quality Measure (UIQM)

UIQM assesses quality of an image by analysing three key aspects of image quality as in equation (3.1): Chroma (UICM), Saturation (UISM), and Contrast (UIConM). The UIQM score typically ranges between 0 and 10. A score closer to 10 suggests that the image has high good contrast and adequate saturation hence making it visually appealing.

$$UIQM = c_1.UICM + c_2.UISM + c_3.UIConM \tag{3.1}$$

Where c1, c2, c3 are constants to balance each metric. In our case, these values are set as 0.0282, 0.2953, 3.5753.

Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE)

Brisque evaluates the perceptual quality of an image without any reference image as in equation (3.2). It analyzes spatial natural scene statistics in the image. The BRISQUE score typically ranges from 0 to 100, where lower scores indicate better image quality, and higher scores indicate poorer quality.

$$I(x,y) = \frac{I(x,y) - \mu(x,y)}{\sigma(x,y) + C} \tag{3.2}$$

Where $I(x,y)$ is the intensity of the pixel at position (x,y), $\mu(x,y)$ is the local mean, $\sigma(x,y)$ is the local standard deviation and C is a small constant to avoid division by zero.

Natural Image Quality Evaluator (NIQE)

NIQE is the Mahalanobis distance between the feature vector μ_{image} and the feature vector $\mu_{natural}$ as in equation (3.3). It typically ranges from 0 to 100, where lower scores indicate better image quality.

$$D(\mu_{\text{image}}, \Sigma_{\text{image}}, \mu_{\text{natural}}, \Sigma_{\text{natural}}) = \sqrt{(\mu_{\text{image}} - \mu_{\text{natural}})^T \Sigma_{\text{natural}}^{-1} (\mu_{\text{image}} - \mu_{\text{natural}})} \quad (3.3)$$

Where μ_{image} is the mean feature vector of the given test image, μ_{natural} is the mean feature vector of high-quality natural images, Σ_{image} is the covariance matrix of the test image's feature vector, Σ_{natural} is the covariance matrix of the feature vectors of the natural images and $\Sigma_{\text{natural}}^{-1}$ is the inverse of the covariance matrix of the natural images.

3.2.2 Reference metrics

Euclidean Distance (NORM)

NORM measures similarity or dissimilarity between images by calculating Euclidean distance between images as in equation (3.4). NORM value of 0 indicates that the images are identical.

$$\|I_1 - I_2\|_2 = \sqrt{\sum_{x,y} |I_1(x,y) - I_2(x,y)|^2} \quad (3.4)$$

Where (x, y) are the pixel coordinates and I_1 and I_2 are input and reference images.

Peak Signal-to-Noise Ratio (PSNR)

PSNR quantifies the difference between the original input image and the processed image as in equation 3.5. A PSNR value above 50 dB is often considered indicative of a high-quality image.

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{R^2}{\text{MSE}}\right) \quad (3.5)$$

Where R is the maximum possible pixel value and MSE is the Mean Squared Error between the input and reference images.

Structural Similarity Index (SSIM)

SSIM measures similarity between two images by considering structural information in images as in equation (3.6). SSIM values lie between -1 and 1 where value of 1 indicates perfect similarity between the two images and 0 with no similarity.

$$\text{SSIM}(I, J) = \frac{(2\mu_I\mu_J + C_1)(2\sigma_{IJ} + C_2)}{(\mu_I^2 + \mu_J^2 + C_1)(\sigma_I^2 + \sigma_J^2 + C_2)} \quad (3.6)$$

Where μ_I and μ_J are the average (mean) intensities of the input and reference images I and J, σ_I^2 and σ_J^2 are the variances of the images I and J, σ_{IJ} is the covariance, C_1 and C_2 are constants used to stabilize the division.

Table 3.1: Metric Evaluation of Figure 2.1

Metrics	ARC	Fusion	Backscatter_Removal	Hazelines	LCMCT	AUTOMSRCR
UIQM	3.0126	2.507	3.612	1.2541	3.1521	4.3588
BRISQUE	33.9199	32.5863	30.2011	40.3075	41.4549	18.3941
NIQE	3.4569	3.4208	3.2906	3.1713	3.2811	3.3536
NORM	0.0658	3.2811	0.0866	0.1185	0.0849	0.0644
PSNR	15.4011	19.1916	10.8636	12.1905	11.7087	9.8171
SSIM	0.4897	0.8632	0.2459	0.3911	0.6226	-0.061

3.3 DataBase

A total of 4,173 images from the UIEB, EUVP, and ChasingDory datasets were utilized to construct the database. 890 images from UIEB dataset, 3195 poor quality images from EUVP unpaired dataset, 70 images from Chasing Dory Rover and a few images from reference papers. Database is carefully handled to choose the best algorithm for a given input image. Steps 4, 5 and 6 of flow chart Figure 3.1 are carried out in this section. The database creation executed as follows:

– Firstly, each image was processed using six underwater image processing algorithms, and evaluated using six quality metric values which are mentioned in section 3.2 as in Table 3.1.

– Some metrics suggest better image quality when they reach a minimum, while others indicate better quality at a maximum. For example, a UIQM score close to 10 and a BRISQUE value near 0 represent better image quality.

– Additionally, these quality metrics range from -1 to 100. In order to determine which algorithm provides better results, it is necessary to find a way to combine all the metrics.

– Metric normalization was performed between 0 and 1 for better clarity. An example of normalized metric values is shown in Table 3.2 for Figure 2.1.

– After normalization, under each metric values all algorithms are compared and assigned scores.

– Finally, the total score for each algorithm was obtained by summing up all the scores under each algorithm as in Table 3.3. This implementation can select the best algorithm for a given input image.

Table 3.2: Normalized Metric Evaluation of Figure 2.1

Norm Metrics	**Norm ARC**	**Norm Fusion**	**Norm_Backscatter Removal**	**Norm Hazelines**	**Norm LCMCT**	**Norm AUTOMSRCR**
UIQM	0.30126	0.2507	0.3612	0.12541	0.31521	0.43588
BRISQUE	0.660801	0.674137	0.697989	0.596925	0.585451	0.816059
NIQE	0.965431	0.965792	0.967094	0.968287	0.967189	0.966464
NORM	0.9342	0.967189	0.999134	0.998815	0.999151	0.999356
PSNR	0.154011	0.191916	0.108636	0.121905	0.117087	0.098171
SSIM	0.74485	0.9316	0.62295	0.69555	0.8113	0.4695

Table 3.3: Obtained Scores on Figure 2.1

Metric Scores	**ARC Scores**	**Fusion Scores**	**Backscatter Removal_Scores**	**Hazelines Scores**	**LCMCT Scores**	**AUTOMSRCR Scores**
UIQM	3	2	5	1	4	6
BRISQUE	3	4	5	2	2	6
NIQE	2	3	5	6	6	4
NORM	5	2	3	2	4	6
PSNR	5	6	2	3	3	1
SSIM	4	6	2	4	5	1
Total	22	23	22	18	**24**	24

However, In the Table 3.3, LCMCT and AUTOMSRCR scores the same. LCMCT scores better with all metrics when compared to AUTOMSRCR. Hence, LCMCT is considered suitable algorithm for Figure 2.1.

3.4 Algorithm selection based on a neural network

EfficientNet weights are used in this work for the algorithm selection. Model implementation is carried out by taking 70% images for training and 15% for validation and 15% for testing.

3.4.1 Strategy to train the model

Training a model with distorted images can create difficulty in understanding features. So, instead of raw images (distorted) white-balanced (removes unrealistic casts) images are given for model training. Transfer Learning is employed with different weights of EfficientNet for algorithm selection.

Table 3.4: Results of Model implementataion

Data	Model	Unfreezed Layers	Batch Size	Epchs	Train Accuracy	Validation Accuracy	Regularisation
raw_image	B0	50	128	50	99.01	61.5	NO
raw_image	B0	50	64	100	99.49	62.78	NO
WB_IMAGE	B0	100	64	100	99.08	60.22	NO
WB_IMAGE	B7	100	64	100	99.25	57.83	NO
WB_IMAGE	B7	100	128	100	96.99	59.11	NO
WB_IMAGE	B7	20	128	75	52.04	39.94	YES

From Table 3.4, it is clear that the model overfits with more epochs and unfrozen layers. L2 Regularization was employed during model training, as shown in Table 3.4, to address overfitting, and it comparatively reduced overfitting.

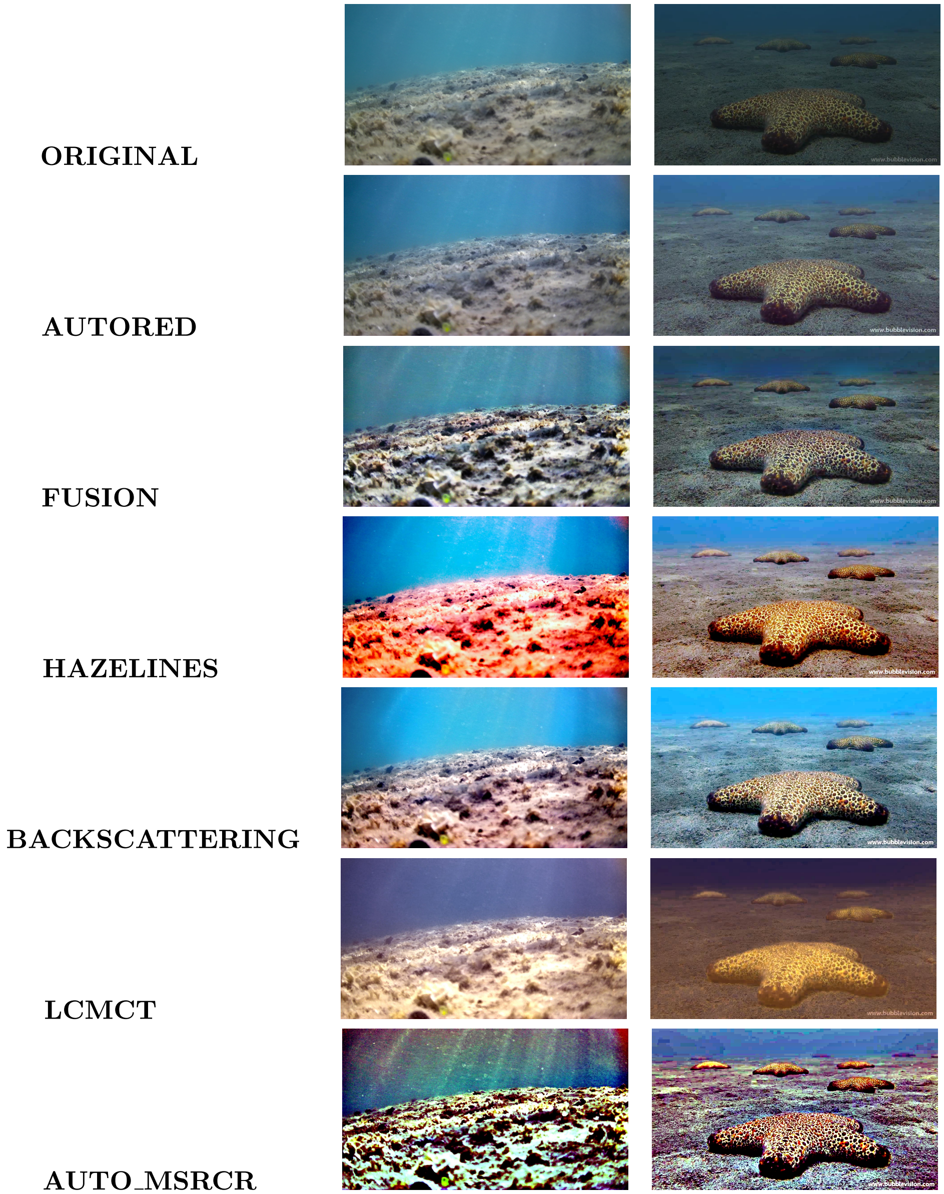

Figure 3.3. *Results of Underwater Image Processing Methods on Chasing Dory and UIEB data*

Chapter 4

Conclusion and Future Work

The project revolves around the challenge of underwater image distortion through the development of a method to automatically choose the best image processing algorithm. This solution can evaluate the quality of a distorted image and recommend the best algorithm that can handle the type and level of distortion by applying a neural network-based supervised classification model on extracted quality metrics. This is indeed an important approach to enhance performances for underwater object detection and environmental monitoring tasks under resource-constrained conditions, as in ROVs. The utilization of a varied dataset such as EUVP and UIEB quite exemplary of a real-world underwater environment, makes it robust and adaptive across multiple aquatic environments. In this process, it has been shown throughout the work how the relevant balance, which needs to be maintained between enhancing image quality and the need for real-time processing, can be achieved through the model developed, which showed promise toward this process. Results show that neural networks can be applied with efficiency to automate the selection of algorithms so as to minimize manual intervention and raise the efficiency of all processes involved. It is in this vista that most likely, the model will be further optimized and find wide applicability in other domains where image distortion has become an important concern. Further research could be carried out on how the incorporation of more sophisticated neural networks and techniques from deep learning can improve performance. The overall work stands as a ground for other works on underwater image processing in the future and therefore forms a worthy contribution to the domain.

Bibliography

[1] Chuan-Yu Chang Li-Chen Fu. Uieb: A benchmark for underwater image enhancement. https://li-chongyi.github.io/proj_benchmark.html, 2019. Accessed: 2024-10-14.

[2] Md Jahidul Islam, Yun Xia, and Junaed Sattar. Euvp: A large-scale dataset for enhancing underwater visual perception. In Proceedings of IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, pages 1–10, 2020.

[3] Kaiming He, Jian Sun, and Xiaoou Tang. Single image haze removal using dark channel prior. In 2009 IEEE Conference on Computer Vision and Pattern Recognition, pages 1956–1963, 2009.

[4] Jarina Raihan A, Pg Emeroylariffion Abas, and Liyanage C. De Silva. Review of underwater image restoration algorithms. IET Image Processing, 13(10):1587–1596, 2019.

[5] Alan Le Boudec, Artur Mkrtchyan, Barbara Džaja, Vincent Rodin, and Hai Nam Tran. Evaluation and optimization of underwater image restoration algorithms. In 2021 6th International Conference on Smart and Sustainable Technologies (SpliTech), pages 1–6, 2021.

[6] Adrian Galdran, David Pardo, Artzai Picon, and Aitor Alvarez-Gila. Automatic red-channel underwater image restoration. Journal of Visual Communication and Image Representation, 26, 11 2014.

[7] Prachi Mathur, Kanasani Monica, and Badal Soni. Improved fusion-based technique for underwater image enhancement. In 2018 4th International Conference on Computing Communication and Automation (ICCCA), pages 1–6, Dec 2018.

[8] Hao Zhang. Removing backscatter to enhance the visibility of underwater object, 2016.

[9] Dana Berman and Shai Avidan. Diving into haze-lines: Color restoration of underwater images. 2017.

[10] Rafał Protasiuk, Adel Bibi, and Bernard Ghanem. Local color mapping combined with color transfer for underwater image enhancement. In 2019 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 1433–1439, 2019.

[11] Sudharsan Parthasarathy and Praveen Sankaran. An automated multi scale retinex with color restoration for image enhancement. In 2012 National Conference on Communications (NCC), pages 1–5, 2012.

[12] R. Sathya, M. Bharathi, and G. Dhivyasri. Underwater image enhancement by dark channel prior. In 2015 2nd International Conference on Electronics and Communication Systems (ICECS), pages 1119–1123, 2015.

[13] Ana Belén Petro, Catalina Sbert, and Jean-Michel Morel. Multiscale Retinex. Image Processing On Line, pages 71–88, 2014. https://doi.org/10.5201/ipol.2014.107.

[14] Mingxing Tan and Quoc V. Le. Efficientnet: Rethinking model scaling for convolutional neural networks, 2020.

[15] Karen Panetta, Chen Gao, and Sos Agaian. Human-visual-system-inspired underwater image quality measures. IEEE Journal of Oceanic Engineering, 41(3):541–551, July 2016.

[16] Anish Mittal, Anush Krishna Moorthy, and Alan Conrad Bovik. No-reference image quality assessment in the spatial domain. IEEE Transactions on Image Processing, 21(12):4695–4708, 2012.

[17] Anish Mittal, Rajiv Soundararajan, and Alan C. Bovik. Making a "completely blind" image quality analyzer. IEEE Signal Processing Letters, 20(3):209–212, 2013.

[18] M. D. Malkauthekar. Analysis of euclidean distance and manhattan distance measure in face recognition. In Third International Conference on Computational Intelligence and Information Technology (CIIT 2013), pages 503–507, Oct 2013.

[19] Zhou Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli. Image quality assessment: from error visibility to structural similarity. IEEE Transactions on Image Processing, 13(4):600–612, 2004.