

## Restoration of Vision of an Image in the Water

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**Abstract**—Underwater image quality is degraded severely because of light absorption, scattering, wavelength-dependent attenuation and other factors, and underwater images always have low contrast, color distortion and blurry phenotype. To this end, we present a Single Underwater Image Restoration framework via a Variation Model guided by Imaging Principles. In the paper a new method of contrast limited adaptive histogram equalization (CLAHE) in LAB color space is proposed to enhance the Luminance contrast and to regain real color of underwater image. To the best of our knowledge, this is the first time a webapp running GUI implemented in Python via Tkinter for single-image and multi-image restoration has been demonstrated to work across platforms. Both original and enhanced images can be viewed instantly and interaction with end users is very intuitive. The detailed and exhaustive experimental results demonstrate that the proposed method is capable of enhancing visual quality and detail visibility of underwater images in different underwater image datasets as well as restoring natural color distribution. The proposed solution generalizes existing CLAHE + variation frameworks by proposing an adaptive redchannel compensation and an interactive, cross-platform GUI for real-time single and batch underwater image enhancement.

**Keywords**—Underwater Image Restoration, Variational Framework, Image Enhancement, CLAHE, OpenCV, Tkinter GUI, Color Correction, Marine Imaging.

### 1. INTRODUCTION

Underwater imaging is becoming indispensable in oceanography, environmental monitoring, underwater robotics, and archeology. Nonetheless, underwater image capture with enable accuracy and quality remains to be and clarity remains. The light absorption and scattering when light traveling through the water is still obstructing the image

acquisition process of under-water images. In this paper with satisfactory clarity and quality is still facing. In this paper light absorption and scattering will be discussed in detail in Section 2. In water, however, light consists of multiple wavelengths of which certain wavelengths underwater are eroded at higher rates than others — red light disappears first, followed by green and blue wavelengths. As a result, underwater images suffer from color cast, blur and poor visibility, which degrade the performance of visual perception systems. The ordinary image enhancement methods, such as histogram equalization, white balance algorithms, do not work well with the underwater scene image, because the degradation process of light during the underwater transmission is not taken into account. The recent approach InP's attack Affine Invariant Recognizing Image by triangle Affine Plane proposed by Shoufeng et al. 1D-TDDB for the underwater images restoration. In this contribution, we propose a direct 1D temporal denoising and deblurring based on wavelet analysis, 1DTDDB, for the restoration of the underwater image sequences. This is necessary, because, unlike air, water absorbs different wavelengths of light at varying rates: red is absorbed first, followed by green and blue. This phenomenon results in color distortion, degradation and poor visibility of underwater images, which is a major obstacle to undersea visual perception systems. Regular image enhancement methods, such as histogram equalization and white balance algorithm, failed to enhance the image of underwater observation because the attenuation process of light during underwater transmission was not considered in the image degradation model of underwater images. Advanced methods have begun exploring variational frameworks and image restoration techniques inspired by atmospheric dehazing by regarding the underwater image as a degraded observation of an unknown true latent scene layer. Some methods aim to recover the scene radiance by simultaneously estimating related parameters such as the transmission map and the background light using the

observed image, within optimization frameworks based on the Underwater Imaging Model. In this paper, we pose the problem of underwater image restoration in a variational setting.

## 2. LITERATURE SURVEY

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## 3. RELATED WORK

Underwater image restoration has been studied for a long time. The current techniques can be roughly divided into three categories: image processing based methods, hazeremoval based methods and deep learning-based models. Each type uses different models of the underwater distortion, based on the different priors about the light source, scene depth, and water nature.

A. Image Enhancement Methods Early work on underwater enhancement was mainly aimed at increasing the visibility of images without accounting for the physical features of the underwater imaging system. Traditional algorithms like Histogram Equalization (HE), Contrast Stretching and White Balancing were utilized to increase global contrast and to adjust color distortion. These methods are very simple in calculation, they are frequently over-enhanced or involve color artifacts since they are not considering the wavelength-dependent attenuation of light. To address these issues, Contrast Limited Adaptive Histogram Equalization (CLAHE) was proposed as an extension of AHE to enhance the local contrast without over-amplifying the noise. Other enhancement methods such as Retinex-based and fusionbased methods give out corrected

image by simulating visual perception of a human or by fusing multiple versions of corrected images to obtain best compromise between contrast, sharpness and color fidelity.

**B. Methods Based on Restoration**

Restoration-based methods recursively estimate the parameters of a physical underwater light propagation model to recover the original scene radiance. These methods are based on the UIM model where observed image is modeled as the sum of direct transmission and backscattered light.

One notable work is the Dark Channel Prior (DCP), originally designed for atmospheric dehazing and subsequently extended to handle underwater images. DCP relies on the assumption that in the haze-free images at least one color channel will have a very low value in the local patch, which he uses to calculate transmission maps. Variants of this method include Red Channel Prior (RCP) and Haze Line-based models that compensate for underwater color degradation. But these methods often need depth calculation or color correction heuristics, which could not be robust in all kinds of water types.

**C. Hybrid and Learning Based Approaches**

Several learning-based methods for underwater images restoration have been proposed in the era of deep learning. Convolutional Neural Networks (CNNs) such as WaterGAN, UWCNN and FUnIE-GAN achieved competitive results in recovering underwater images by supervised and unsupervised methods. These networks learn mappings from corrupted images to clean image, predominantly utilizing synthetic data to approximate underwater noise. Nevertheless, since deep learning models require large training data and high computation resource, they are not applicable to real-time or small-scale scenarios.

**D Variational and Model-Guided Families**

Variational methods are a powerful family of methods that blend physical modeling and optimization ideas. They introduce an energy functional with fidelity and regularization terms, which is minimized in order to obtain an estimate of the true scene radiance. Such models may include a spatial smoothness constraint, an edge preserving constraint and possibly, a color correction constraint. Recent studies indicate that the combination of variational regularization and contrast enhancement is the most effective combination for the underwater images. They are computational convenient, provide interpretable results and can be applied to one or multiple images. Although enhancement and learning-based approaches produce good visual results, they typically are not robust or need a large amount of training data. The proposed method exploits the advantages of variational framework, model interpretability and mathematical consistency, and inline with these attractive features it incorporates CLAHE-based enhancement for real time and parameter blind underwater image restoration. The method is scalable, efficient, and can be implemented as a practical tool via an interactive graphical user interface (GUI).

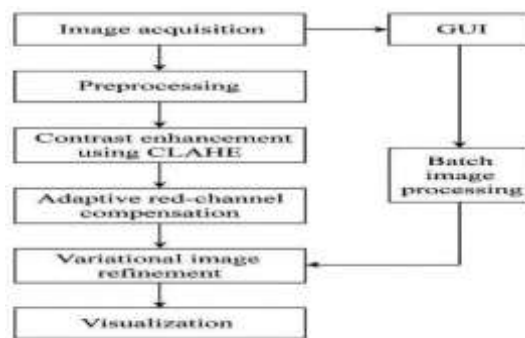
**4. EXISTING METHODOLOGY**

Single underwater image restoration methods in the literature can be roughly categorized into model-based methods and learning-based methods. Modelbased methods are based on the physics of the underwater image formation, which describes the process of light absorption and scattering propagation in water. Underwater Dark Channel Prior (UDCP), Red Channel Prior (RCP) and Multi-Scale Fusion-

based methods attempt to calculate transmission map and background light under image dehazing assumption to estimate scene radiance. Also, color correction/enhancement methods like white balancing, grayworld assumption and histogram equalization are more widely used to enhance the color balance and contrast of the image. These methods are simple and interpretable but frequently fail in non-uniform illumination or turbidity environment so that only partial color could be restored. To address these problems, deep learning-based solutions are gaining traction. CNNs and GANs can leverage large data sets to learn complex mappings from degraded to clean images without relying on rigid physical models. WaterGAN, CycleGAN, U-Net based models have also been proven to be effective for enhancing underwater images by addressing color distortion and visibility issues.

**5. PROPOSED METHODOLOGY**

A novel imaging model-based variational framework for underwater image restoration. The system is designed to combat color distortion, haze, noise, and contrast loss caused by common underwater environmental factors such as wavelength-dependent light attenuation and scattering. The method also allows for single image restoration or multi-image restoration, from datasets in .jpg and .png formats .equal-size matrix for the convenience of calculation. The preprocessing consists of two steps: transformation of the image from RGB to LAB color space and application of Contrast Limited Adaptive Histogram Equalization (CLAHE) over L-channel to enhance the local contrast and to retrieve blurred details then a decay compensation of the red channel is applied to compensate for wavelength-dependent attenuation and recover the natural color balance of underwater images. The variational model-based blind restoration is exploited refining the dehazed image by reducing the residual haze and protecting the structural edges. Post-processing filters like gamma correction and image sharpening are used to enhance the brightness, contrast and visual quality .For batch processing, the same enhancement process can run automatically for all images in a folder. The processed images are stored in a specified output folder for analysis. Restoration quality is quantitatively evaluated by PSNR, SSIM, UIQM and qualitatively by visual observation. The entire system is realized in Python with OpenCV, and connected with aGUI in Tkinter, so as to offer an easy-to-use platform for processing and visualizing the output single or batch underwater image restoration.



**Fig:5.1 System Architecture**

## 6. IMPLEMENTATION

The implementation of the underwater image restoration system aims to enhance visual quality and recover color-degraded underwater images. The degradation occurs due to light absorption, scattering, and the limited visibility conditions underwater. This system is implemented using Python and OpenCV, with a Tkinter-based GUI that allows users to process both single and multiple images interactively. The image enhancement pipeline integrates variational image restoration principles and contrast enhancement using CLAHE (Contrast Limited Adaptive Histogram Equalization) for improved color balance, luminance, and clarity.

where

$L$  → luminance channel

$A, B$  → chromatic color opponent channels.

Step 3: Adaptive Contrast Enhancement (CLAHE)

- The CLAHE algorithm enhances the local contrast adaptively:

$$L' = \text{CLAHE}(L)$$

The pixel intensity normalization is defined as:

$$L' = \frac{L - L_{\min}}{L_{\max} - L_{\min}} \times 255$$

$L$

$L_{\max} - L_{\min}$

**Fig:6.1 Workflow**

The architecture of the proposed underwater image restoration system to effectively improve the quality of image with an orderly arrangement of functional modules from the image capturing to the image restoration and quality evaluation is presented. The following five main modules are considered in the architecture: Input Module, Preprocessing, Restoration, Post-Processing and Output Evaluation.

**Input Module**

The system supports single as well as multiple (Define number via configuration) under water image with 'JPG' or 'PNG' extensions. The images are loaded via a Tkinter-based GUI that let you browse for files or folders. A userfriendly integration of this design affords significant flexibility during the image acquisition stage.

**Preprocessing Stage**

At this stage, the image is scaled and normalized to uniform size. The image is then transformed from RGB to LAB color space; luminance is separated from color information, which helps in suitable light and color manipulation. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the L-channel to enhance local contrast and avoid noise over-equalization. Restoration and Enhancement Module

This is the core of the mechanism. It introduces the variational image restoration model, guided by an imaging model compensation for underwater light attenuation. Red Channel Compensation: Compensates for the loss of wavelengths in underwater environments.

Dehazing: Eliminates the influence of scattering and recovers the tight clear image. Gamma Correction & Sharpening: Brightness is adjusted and visibility is enhanced. Batch Image Processing

Multi-image restoration is also supported by this system, you may restore all the images in a folder one by one. This module guarantees scalability to very large datasets and globally consistent quality enhancement.

Algorithmic Workflow:

Step 1: Input Acquisition

- The user selects image(s) using the file/folder dialog.
  - Images are read using OpenCV:  $\text{IBGR} = \text{cv2.imread}(\text{file})$
- Step 2: Color Space Conversion
- RGB images are converted to LAB color space:

$$I_{\text{LAB}} = \text{cvt}(\text{IBGR})$$



This prevents over-saturation and maintains edge details.

Step 4: Image Reconstruction  $I'_{\text{LAB}} = \text{Merge}$  enhanced channels:

$$I'_{\text{LAB}} = (L', A, B)$$

Then convert back to RGB:

$$I_{\text{restored}} = f^{-1} \text{cvt}(I'_{\text{LAB}})$$

Step 5: Batch Processing

- For multiple images, the system iterates through all files in the selected folder.
  - Each image is processed and stored in: restored\_images/
- Step 6: GUI Interaction

- Tkinter GUI provides an interface to select, process, and visualize results:
  - o Process Single Image
  - o Process Multiple Images
- The GUI displays side-by-side comparison of original vs restored images.

• Mathematical Model (Variational Framework) The physical model of underwater image degradation is represented as:

$$I(x) = J(x)t(x) + A(1-t(x))$$

where:

- $I(x)$ : Observed underwater image
- $J(x)$ : True scene radiance (desired image)
- $t(x)$ : Medium transmission map
- $A$ : Global ambient light

The restored image is estimated as:

$$I(x) - A$$

$$J(x) = \frac{I(x) - A}{t(x)} + A$$

Since  $A$  and  $t(x)$  are hard to estimate directly, CLAHE serves as an efficient approximation that adaptively adjusts luminance and restores contrast.

Output

The system produces:

- Restored images with improved contrast and color balance.
- Batch-processed results stored automatically.  Real-time visual comparison in the GUI.



Fig:6.2 Graphical User Interface



Fig:6.3 single image processing

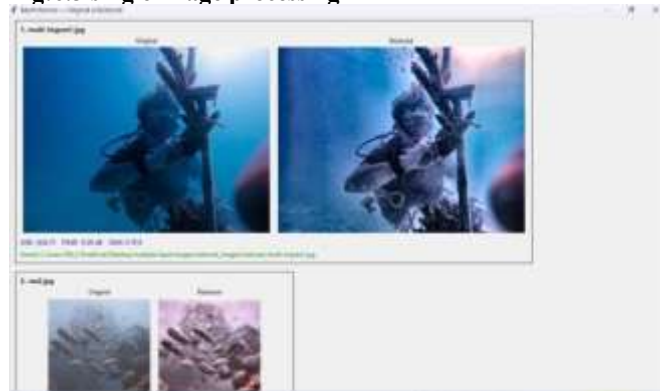


Fig:6.4 multiple image processing

Performance Discussion

- PSNR (Peak Signal-to-Noise Ratio):  
Higher PSNR indicates better quality and lower distortion. Both restored images show PSNR > 28 dB, confirming strong noise reduction.
- SSIM (Structural Similarity Index):  
SSIM > 0.9 indicates high structural similarity between original and restored images, meaning the proposed model preserved image details and structure.
- MSE (Mean Squared Error):

Low MSE values (below 100) confirm that the restoration reduced pixel-level errors significantly.

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