# Enhancing 3D Reconstructions in Underwater Environments: The Impact of Image Enhancement on Model Quality

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## Abstract

3D reconstructions in underwater environments face significant challenges due to poor image quality, caused by blurring, reduced contrast, color distortion, and inadequate lighting. This study investigates the impact of various image enhancement techniques on underwater 3D reconstruction, focusing on Contrast Limited Adaptive Histogram Equalization (CLAHE), RGB Histogram Stretching (RGHS), and a combined approach integrating RGB stretching with CLAHE. Three real-world underwater datasets were analyzed to assess the effectiveness of these methods in improving the accuracy and completeness of reconstructed 3D models. Notably, the RGB-CLAHE combination achieved the most substantial improvements, increasing reconstructed points by 7.60%, detected features by 7.56%, and reconstructed features by 12.94% on average across the datasets. However, the enhancement methods did not improve performance in certain cases, underscoring the need for a robust evaluation methodology to determine the most suitable technique for each dataset. These findings support the design and development of adaptive evaluation frameworks alongside advanced enhancement strategies, enabling more accurate and detailed analysis of submerged environments. Such approaches have the potential to benefit a wide range of scientific and industrial applications, including marine research, underwater archaeology, and inspection tasks.

## 1. Introduction

3D reconstruction of underwater sites has become an increasingly important tool in fields such as maritime archaeology, marine biology, and environmental monitoring. In recent years, there has been a growing trend toward using photogrammetry-based methods, driven by the accessibility of high-resolution imaging equipment and open-source software solutions. However, underwater imaging remains inherently challenging due to factors like light attenuation, color distortion, scattering, and turbidity, all of which compromise image clarity and, consequently, the quality of the resulting 3D models. As a result, a significant research focus has emerged around pre-processing techniques, particularly image enhancement methods to mitigate these issues and improve reconstruction outcomes. Another notable trend is the shift toward automating parts of the reconstruction pipeline and integrating machine learning to optimize feature matching and depth estimation. The primary objective is to produce a 3D model that accurately represents the real-world object, capturing its geometry and details as faithfully as possible.

To complement the core photogrammetric workflow, several methods have been developed to enhance the quality and reliability of underwater 3D reconstructions. These include image preprocessing techniques such as histogram equalization (Yin et al. (2025)), dehazing ( Goyal et al. (2024)), and contrast enhancement (van Nijnatten et al. (2024)), which aim to restore visual features lost due to poor underwater visibility. In addition, improvements in camera calibration (Yang et al. (2024)), artificial lighting (Zhou et al. (2024)), and structured acquisition strategies, such as predefined diver trajectories or the use of reference grids help reduce inconsistencies in image capture. There is also a growing interest in integrating navigation and positioning systems, such as micro geodesic networks or inertial measurement units (IMUs) (Vrochidis et al. (2021)), to provide spatial accuracy and support scale-aware reconstructions. These auxiliary approaches collectively address many of the challenges posed by underwater environments and are becoming standard components of modern underwater survey and modeling workflows.

Despite their advantages, the secondary methods used to support underwater 3D reconstruction are not without limitations. Image enhancement techniques, while effective in improving visual clarity, can introduce artifacts or alter key features, potentially leading to inaccurate reconstructions or distorted geometries. Similarly, methods like contrast stretching or dehazing may improve human visual perception but negatively affect the performance of feature-matching algorithms if not properly calibrated. Structured acquisition strategies require strict adherence during fieldwork, which is often difficult to achieve in dynamic underwater environments influenced by currents, visibility changes, and diver movement. Moreover, positioning systems such as geodesic networks and IMUs, though beneficial for spatial accuracy, add complexity, cost, and logistical constraints to underwater survey missions. These challenges highlight the need for adaptable and well-balanced preprocessing approaches that enhance image quality without compromising the integrity of the 3D reconstruction process.

This study addresses the persistent challenge of balancing image enhancement with reconstruction accuracy in underwater photogrammetry, a problem that is often overlooked in existing literature. While previous research has explored enhancement techniques individually, there is a lack of systematic evaluations that measure their impact on actual 3D reconstruction outcomes, particularly across diverse real-world underwater conditions. The novelty of this work lies in its reconstruction-centered comparative framework, which moves beyond perceptual or visual assessments to evaluate how enhancement directly influences 3D model quality. Key contributions of this study in-

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clude:

- A systematic, metric-driven evaluation of multiple enhancement methods, focusing on their effect on the accuracy and completeness of 3D reconstructions;
- The use of three heterogeneous underwater datasets, each representing distinct environmental conditions, to assess generalizability;
- The integration of qualitative and quantitative assessments, including visual inspection of point clouds and reconstruction metrics to measure impact;
- A reproducible pipeline based on OpenSfM that demonstrates the practical implications of preprocessing on real-world underwater imagery;

The remainder of this paper is organized as follows. An overview of the related research is provided in Section 2, while Section 3 includes details about the evaluation 3D reconstruction methodology. Section 4 contains the experimental evaluation, and Section 5 provides the conclusions alongside future improvements and limitations.

## 2. Related Works

Underwater image acquisition presents unique challenges due to the physical properties of the aquatic environment, such as light attenuation (Li et al. (2024)), scattering, and absorption, which lead to significant image degradation. These phenomena cause common issues, including reduced visibility, blurring, and severe color distortions (Wang et al. (2024)), particularly the loss of red wavelengths, resulting in low-contrast and visually inconsistent images. Such degradations directly hinder the performance of computer vision tasks, especially 3D reconstruction (Pan et al. (2025)), where accurate feature detection, depth estimation, and texture mapping are crucial. The inconsistent illumination and lack of reliable visual cues in underwater imagery make traditional reconstruction techniques less effective, necessitating specialized approaches to enhance image quality and maintain robustness in these adverse conditions.

Underwater image enhancement methods aim to improve visual quality by correcting color and contrast distortions caused by light absorption and scattering Zhang et al. (2022). Histogram-based techniques like CLAHE (Mehdizadeh et al. (2023)) efficiently redistribute pixel intensities to balance image contrast, making them suitable for real-time use. For example, RGHS (Huang et al. (2018)) combines adaptive contrast and color correction in RGB and Lab spaces to enhance shallow-water images with reduced noise. Fusion-based methods (Song and Wang (2021)) integrate multiple enhancement strategies such as contrast adjustment, color correction, and dehazing for more robust results. Retinex-based approaches mimic human visual perception (Zhang et al. (2017)) by separating illumination from reflectance, effectively restoring natural colors under varying lighting conditions.

Underwater 3D reconstruction is a challenging yet essential task for a variety of applications, from marine biology to underwater archaeology Di Angelo et al. (2022). Common approaches include Structure-from-Motion (SfM) Yakar and Dogan (2019) and stereo vision Tian et al. (2022), both of which rely on capturing multiple images or video frames to estimate the 3D structure of a scene. Vrochidis et al. (2025) enhanced 3D reconstruction in challenging underwater environments by utilizing intelligent colormap selection, thereby improving the performance of OpenSfM in such conditions. Similarly, Dimara et al. (2024) explored the integration of mixed reality and 3D modeling for cultural heritage preservation, showing how these techniques can be applied to above-water and underwater scenarios, improving accuracy and detail in reconstructions. In addition, tools such as OpenMVS Li et al. (2020) and OpenMVG Li et al. (2022) have been utilized in many underwater 3D reconstruction tasks, offering open-source solutions for multiview stereo reconstruction, with improvements focused on noise reduction and depth estimation in murky underwater environments. These efforts contribute to the advancement of the reliability and precision of underwater 3D modeling despite inherent visual challenges.

Several studies have shown that image enhancement can significantly impact the accuracy of 3D reconstruction by improving feature visibility, detection, and matching (Hou and Ye (2022)).Mangeruga et al. (2018) conducted a comprehensive benchmarking of five state-of-the-art underwater image enhancement methods using diverse datasets with varying depth, turbidity, and lighting conditions. Preprocessing steps such as contrast correction, dehazing, and color balancing often lead to more consistent and complete reconstructions, especially in visually degraded environments like underwater scenes (Espinosa et al. (2023)). However, there is still a noticeable lack of comprehensive evaluations that compare the effectiveness of various enhancement techniques on real underwater datasets. This limits our understanding of which methods are most beneficial and highlights the need for systematic benchmarking in realistic underwater conditions.

Although several works have proposed image enhancement techniques to support underwater 3D reconstruction, most studies focus narrowly on individual methods or specific environments without conducting broad, comparative evaluations. For instance, some research demonstrates improvements in feature matching and reconstruction accuracy using enhanced images, but these are often limited to controlled or synthetic datasets, which do not fully reflect the challenges of real underwater scenes. In addition, there is a lack of standardized benchmarks and consistent quantitative evaluation across different enhancement pipelines and reconstruction frameworks. Many approaches also fail to assess performance under varying conditions such as depth, turbidity, and lighting. These gaps highlight the need for a more comprehensive study that systematically evaluates multiple enhancement methods in real-world underwater datasets. The proposed work addresses this by analyzing how different enhancement techniques affect the quality and accuracy of 3D reconstructions, providing insight into their practical value for real underwater imaging scenarios.

## 3. Methodology

The proposed methodology follows a structured pipeline designed to assess the impact of image enhancement on underwater 3D reconstruction. It begins with the acquisition of raw underwater images, which typically suffer from distortions such as low contrast, blurring, and color cast due to water scattering and absorption. These images are first processed using a variety of enhancement techniques aimed at improving visibility and color balance. The enhanced images are then subjected to feature detection algorithms, which identify keypoints necessary for constructing 3D models. Using these detected features, 3D reconstruction is performed through OpenSfM (Vrochidis et al. (2025)). Finally, the output reconstructions are quantitatively and qualitatively evaluated using metrics that assess visual quality, completeness, and geometric accuracy, allowing for a comprehensive analysis of how enhancement influences reconstruction performance. For better understanding, a schematic overview of the entire pipeline is provided in Figure 1.

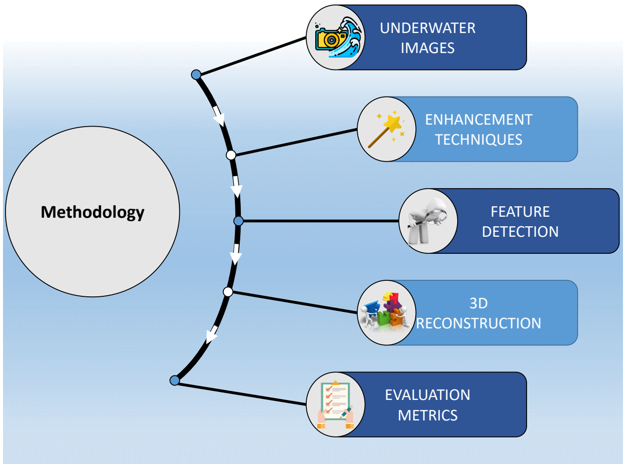


Figure 1. Architecture of the enhancement-assisted 3D reconstruction approach

### 3.1 Image Enhancement Techniques

Image enhancement plays a pivotal role in underwater imaging by improving the visibility of details that are often obscured due to the challenging conditions of the underwater environment. Preprocessing techniques enhance the overall quality of the images, bringing out hidden features and correcting distortions such as color imbalance, low contrast, and blur. The primary objective is to generate a clearer and more accurate representation of the underwater scene. As the first step in the methodology, image enhancement aids in increasing the consistency and quality of keypoint matches between images, thereby improving the subsequent stages of feature detection and 3D reconstruction.

CLAHE (Mehdizadeh et al. (2023)) is a popular image enhancement technique designed to improve the contrast of an image, especially in regions with low visibility, without over-amplifying noise. Unlike traditional histogram equalization, which globally adjusts contrast, CLAHE works locally by dividing the image into small tiles and performing histogram equalization on each tile. This localized approach prevents over-enhancement in homogeneous regions and ensures that details in darker or brighter regions are visible. The contrast limiting parameter $C$ is used to clip the histogram and prevent excessive contrast enhancement, while the size of the tiles determines the level of local contrast adjustment. The CLAHE formula is given by:

$$\text{New intensity} = \frac{(I - \text{min intensity})}{(\text{max intensity} - \text{min intensity})} \times (L-1), \tag{1}$$

where $I$ is the original intensity of the pixel, *min intensity* and *max intensity* are the minimum and maximum intensities in the local tile, and $L$ is the total number of possible intensity levels. For CLAHE, the local histograms are clipped based on a predefined limit $C$, and the clipped histograms are redistributed to adjust the contrast while avoiding over-enhancement. This method is particularly useful in underwater images, where light attenuation and scattering often result in uneven lighting and poor contrast.

Another popular method for enhancing underwater images is the RGHS (Huang et al. (2018)). RGHS is designed to correct the contrast and color distortion typically observed in underwater images caused by light absorption and scattering. The method works by first performing contrast correction in the RGB color space, followed by a color correction step in the CIE-Lab color space. The contrast correction is achieved by equalizing the Green ($G$) and Blue ($B$) channels and then dynamically redistributing the histograms of each R-G-B channel based on the intensity distribution of the original image and the wavelength attenuation of different colors underwater. This process is guided by dynamic parameters that are adaptive to the specific image content, which helps to enhance the contrast without over-amplifying noise. The bilateral filter is often used to smooth the image while preserving edges and important details. For color correction, the '$L$' component (luminance) in the CIE-Lab color space is stretched, while the '$a$' and '$b$' components (representing color balance) are adjusted to achieve a natural appearance. The RGHS method is composed of two main stages, which include contrast and color correction. In the first stage, contrast is adjusted in the RGB color space using a formula similar to Equation 1, which stretches the histogram based on the intensity distribution and wavelength-dependent attenuation of different color channels. In the second stage, color correction is performed in the CIE-Lab color space using the following formula:

$$O_x = I_X \cdot \left( \Phi^{1-\left|\frac{I_C}{128}\right|} \right), \quad C \in \{a, b\}, \tag{2}$$

where $O_x$ and $I_x$ denote the output and input pixel values, respectively. $I_C$ represents the value of the 'a' or 'b' component in the CIE-Lab color space, which is in the range of [-128, 127]. The constant $\Phi$ controls the degree of color adjustment. This formulation adapts the correction based on the chromatic deviation of each pixel, ensuring more balanced and natural color enhancement across the image.

After evaluating individual preprocessing techniques, a fusion-based approach combining RGB stretching (Ghani and Isa (2015)) and CLAHE was explored for enhanced underwater image enhancement. This combined method aims to leverage the strengths of both techniques. RGB stretching improves global contrast by expanding the histograms of the red, green, and blue channels across the full intensity range, while CLAHE enhances local contrast and preserves fine details. In RGB stretching, each color channel is adjusted independently to compensate for the unequal attenuation of light in water, which varies by wavelength. For example, red fades first at around 5 meters, followed by orange at 10 meters, yellow at 20 meters, green at 30 meters, and blue at approximately 60 meters. This physical phenomenon results in color imbalance and loss of detail in underwater imagery. By applying RGB stretching first, the global contrast is improved, and then CLAHE further refines the image by amplifying local features without introducing excessive noise. The formula for RGB stretching is given below:

$$P_{\text{out}} = (P_{\text{in}} - I_{\min}) \cdot \left( \frac{O_{\max} - O_{\min}}{I_{\max} - I_{\min}} \right) + O_{\min}, \tag{3}$$

where $P_{\text{in}}$ and $P_{\text{out}}$ represent the input and output pixel values, respectively. $I_{\min}$ and $I_{\max}$ are the minimum and maximum intensity level values in the input image, while $O_{\min}$ and $O_{\max}$ define the desired intensity range for the output image.

### 3.2 Reconstruction and Evaluation Process

OpenSfM is the open-source structure-from-motion (SfM) library that was used for multi-view 3D reconstruction from images. It supports various camera models and utilizes robust computer vision techniques to reconstruct sparse point clouds and estimate camera poses. The reconstruction process begins with feature detection, where OpenSfM employs the Scale-Invariant Feature Transform (SIFT) to detect distinctive keypoints in each image. These keypoints are invariant to scale and rotation, allowing reliable matches across different viewpoints. Descriptors are computed to uniquely characterize each detected keypoint. For instance, in the case of the SIFT algorithm, the descriptor is constructed as follows:

$$d(x, y) = \{f_1(x, y), f_2(x, y), \ldots, f_n(x, y)\} \tag{4}$$

In this context, *d(x,y)* represents the descriptor, where each $F_\text{i}(x, y)$ corresponds to the *i-th* feature value extracted from the image at the keypoint located at *(x,y)*. These feature descriptors are compared across images to identify matching keypoints, allowing the system to establish correspondences between different viewpoints. For keypoints *i* and *j* detected in two separate images, the descriptor matching process proceeds as follows:

$$M(i, j) = \arg\min_{J} \{\|D_i - D_J\|\} \tag{5}$$

In this equation, *M(i,j)* represents the match between keypoints *i)* and *j*, where $D_i$ and $D_j$ are their respective feature descriptors. The term $\|D_i - D_j\|$ denotes the Euclidean distance between these descriptors, and $arg_{min}$ identifies the keypoint *j* whose descriptor is most similar to that of keypoint *i*. This descriptor-matching process is essential for constructing a sparse point cloud, as it forms the basis for accurate geometric reconstruction. OpenSfM handles large-scale datasets effectively by applying robust outlier rejection techniques such as Random Sample Consensus (RANSAC), which filters out mismatches caused by noise, occlusion, or scene ambiguity.

Following the keypoint matching and outlier rejection, OpenSfM proceeds to estimate the relative camera poses using incremental structure-from-motion techniques. It refines these poses through bundle adjustment, a global optimization process that minimizes the reprojection error across all views. Once the camera positions and orientations are accurately determined, the software performs triangulation to generate a sparse 3D point cloud from the matched features. The OpenSfM process for 3D reconstruction is described in Algorithm 1.

In evaluating the quality and effectiveness of underwater 3D reconstruction without access to ground truth models, three key metrics were selected: Detected Features (DF), Reconstructed Features (RF), and Reconstructed Points (RP). DF represents

**Algorithm 1** 3D Reconstruction Pipeline Using OpenSfM

**Require:** A collection of overlapping 2D images
**Ensure:** A reconstructed 3D point cloud model
Extract local features (e.g., SIFT) from each image
Perform feature matching between image pairs to find point correspondences
Use RANSAC to eliminate outliers and retain geometrically consistent matches
Estimate camera poses incrementally using PnP and global optimization
Triangulate matched keypoints to generate a sparse 3D point cloud
Optionally apply multi-view stereo (MVS) to obtain a dense reconstruction
Optimize the structure and motion through bundle adjustment
Export the reconstructed model in a suitable 3D format (e.g., .ply, .obj)
**return** Final 3D point cloud

the total number of image features detected by the feature extraction algorithm, reflecting the richness of information available in the input images. RF measures how many of these features were successfully matched and incorporated into the final 3D structure, indicating the effectiveness of both the feature-matching and triangulation steps. RP refers to the total number of 3D points generated in the reconstruction, serving as an indicator of the spatial completeness and density of the resulting model. These metrics were chosen because they provide a quantifiable assessment of reconstruction quality in scenarios where geometric accuracy cannot be directly measured due to the absence of a reference 3D model, particularly in real-world underwater environments.

To evaluate the impact of different enhancement methods on 3D reconstruction, a comparative analysis was conducted by applying each preprocessing technique to the same set of underwater images and then processing them through a consistent reconstruction pipeline. Unprocessed images were used as a baseline to assess the relative performance of each method. All reconstruction experiments were performed using identical settings, including fixed parameters for feature detection, matching, and bundle adjustment to ensure fair comparisons. This controlled setup allowed for a reliable assessment of how each enhancement method affects the quality and completeness of the final 3D model.

## 4. Experimental Evaluation

The experimental evaluation provides a comprehensive overview of the datasets used, along with implementation details to ensure the reproducibility of the experiments. Furthermore, the section presents the results obtained from the conducted experiments using quantitative metrics, including the number of reconstructed points, detected features, and reconstructed features. In addition to the numerical results, a detailed analysis of the observed patterns across different datasets and preprocessing strategies is offered. Particular attention is given to both consistent trends and dataset-specific deviations, offering insights into the strengths and limitations of each method under varying conditions.

### 4.1 Dataset

To ensure a robust and comprehensive analysis, three distinct underwater image datasets were utilized in this study. While all datasets capture submerged environments, each represents different underwater conditions, including variations in depth, lighting, turbidity, and seabed composition. This diversity was intentionally selected to evaluate the performance and adaptability of the applied methods across a range of realistic underwater scenarios. By incorporating datasets from multiple underwater settings, the study enhances the generalizability of the findings and ensures their applicability to varied environmental contexts.

Dataset A comprises 280 underwater images captured at a depth of 30 meters. These images, along with those from a second dataset, document an underwater artifact concentration. The second dataset (Dataset B) consists of approximately 200 underwater images captured at a site geographically close to that of the first dataset. While both datasets share similar depth and environmental conditions, Dataset B is distinguished by its unique scene composition. This spatial configuration introduces additional structural complexity and surface variation, making it a valuable case for evaluating the robustness of preprocessing techniques and 3D reconstruction algorithms.

In addition to the two real-world underwater datasets, a third dataset (Dataset C) was employed to further assess the performance of various preprocessing methods under diverse environmental conditions. The Mermaid Underwater Dataset (Avanthey and Beaudoin, 2024) comprises underwater images captured at a depth of approximately 20 meters at the La Sirène site in Saint-Raphaël, France, during the Submeeting 2022 underwater robotics workshop. It consists of 321 underwater images and covers an area of roughly 150 m² with sub-millimeter ground sampling distance (GSD) and features a variety of underwater scenes, including a mermaid statue, a sandy plain with scattered stones, and a rocky zone inhabited by marine life. Images were acquired by divers using a single camera under natural lighting conditions and are provided without any preprocessing.

Figure 2 presents an overview of a dataset (Dataset C) used in this study, showcasing representative input images alongside their corresponding 3D reconstruction, generated without the application of any preprocessing techniques. The reconstruction is visualized as a point cloud derived directly from the image data. This visualization provides a qualitative comparison of scene complexity and the fidelity of a 3D reconstruction.

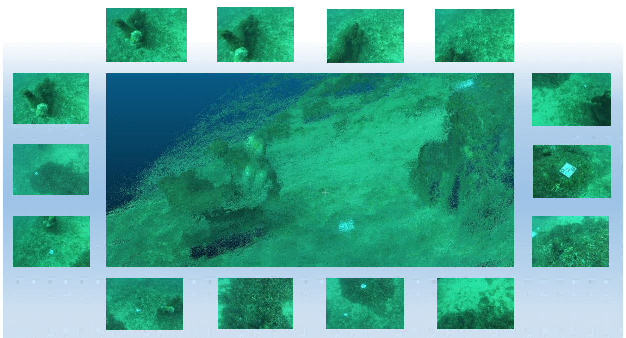

Figure 2. Overview of Dataset C, one of the datasets utilized for experimental validation.

## 4.2 Implementation details

The implementation specifications for this study included configuring the parameter $\phi$ to a value of 1.3 for the RGHS method. For the CLAHE method, the processing parameters consisted of a rectangular grid with a tile size of (4, 4) and a clip limit set to 2. These hyperparameters were selected based on iterative tuning and validation to achieve optimal visual enhancement and reconstruction quality.

All experimental procedures were executed without issues using four CPU threads. The reconstruction pipeline was built on OpenSfM, an open-source photogrammetry library primarily optimized for CPU usage. Its SfM core relies on the Ceres Solver for bundle adjustment and optimization, which does not support GPU acceleration. Similarly, the depth map estimation components in OpenSfM are also CPU-bound and are not designed to leverage GPU hardware. As a result, OpenSfM operates entirely on the CPU without any GPU acceleration requirements.

All experiments were conducted on a workstation equipped with an Intel i5-10600K CPU, 16 GB of RAM, and an NVIDIA RTX 1660 GPU. Although a dedicated GPU was available, it remained unused throughout the processing pipeline due to the CPU-centric nature of the software. This setup highlights the accessibility of the workflow, as it does not depend on high-end GPU resources, making it feasible for deployment in environments with limited computational infrastructure.

## 4.3 Results

First, visual examples of the applied enhancement methods were made across all images. These visualizations serve to qualitatively demonstrate the effects of each method, such as CLAHE, RGHS, and RGB-CLAHE, on the underwater imagery. By comparing the original and enhanced images side by side, the impact on contrast, brightness, and feature visibility becomes more evident. These visual comparisons help illustrate how each method modifies the input images, potentially influencing feature detection and point cloud reconstruction in subsequent stages. Including different image samples also highlights how the same enhancement technique may produce varying visual outcomes depending on the specific environmental conditions, such as depth, lighting, and water clarity. This visual analysis complements the quantitative results and supports the discussion on the suitability of different methods for varying underwater scenarios. These enhancements are presented in Figure 3.

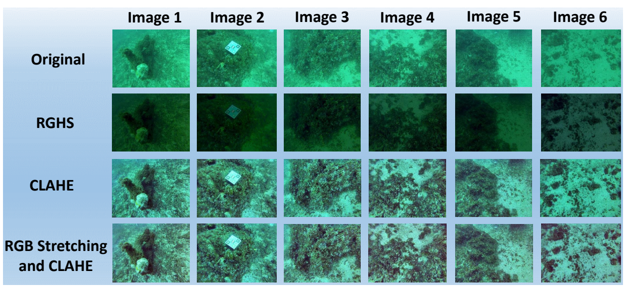


Figure 3. Visualization of the enhancement methods.

For Dataset A, the unprocessed images generated a 3D model consisting of 762,431 reconstructed points, 14,563 features, and 6,156 reconstructed features. Applying CLAHE (Contrast Limited Adaptive Histogram Equalization) enhanced the reconstruction, increasing the number of reconstructed points by 9.65%, features by 18.96%, and reconstructed features by 14.25%. In contrast, the RGHS method did not yield improvements over the unprocessed baseline. The combination of RGB stretching and CLAHE produced the best results, with improvements of 10.97% in reconstructed points, 24.62% in features, and 22.39% in reconstructed features. Among all tested preprocessing techniques, this combination proved most effective for enhancing 3D reconstruction.

Next, Dataset B was evaluated to determine whether it exhibited similar characteristics to Dataset A. The trends observed for Dataset B were comparable to those of Dataset A, which can be attributed to their shared characteristics, such as depth and water visibility. The unprocessed images produced a 3D point cloud with 435,918 reconstructed points, 12,290 detected features, and 5,883 reconstructed features. After applying CLAHE, these values increased by 2.40%, 2.25%, and 0.98%, respectively. Once again, the RGHS method did not yield better results than the unprocessed data. The best performance was achieved by combining RGB stretching and CLAHE, which significantly improved the reconstruction. This combination demonstrated its effectiveness, especially for datasets with similar characteristics and depth, such as Datasets A and B. Specifically, the reconstructed points increased by 7.70%, the detected features by 7.74%, and the reconstructed features by 10.46%.

For the Mermaid dataset, different results were observed compared to Datasets A and B. The unprocessed images produced the best results, with 264,790 reconstructed points, 13,556 detected features, and 2,991 reconstructed features. While applying CLAHE improved the results, it did not surpass the unprocessed data. As in the previous datasets, the RGHS method performed the worst, yielding inferior metrics. However, the combination of RGB stretching and CLAHE produced the best results among the enhancement methods, even though it resulted in a decrease of -2.31% in reconstructed points, -10.94% in detected features, and -2.01% in reconstructed features. This drop can be attributed to the specific characteristics of the Mermaid dataset, which was captured in shallower depths compared to the previous datasets and contained only one object for reconstruction. Datasets with a greater number of objects tend to yield better results with enhancement techniques, as more features are generated, allowing the enhancements to have a more significant impact. Fewer objects, as seen here, limit the number of features, which in turn affects the enhancement effectiveness.

Unfortunately, due to the absence of ground truth models for these real-life underwater datasets, the metrics presented here were the most reliable option for evaluating the efficiency of the enhancement methods. To provide a generalized overview of the results, a summary table is included. The unprocessed images produced a total of 1,463,139 reconstructed points, 40,409 detected features, and 15,030 reconstructed features. The application of CLAHE resulted in improvements of 3.75%, 5.09%, and 4.38% for reconstructed points, detected features, and reconstructed features, respectively. The RGHS method, however, did not yield any noticeable improvements compared to the unprocessed data. In contrast, the combination of RGB stretching and CLAHE achieved the most significant enhancements, increasing the reconstructed points by 7.60%, the detected features by 7.56%, and the reconstructed features by 12.94%. The results are presented in Table 1.

The results indicate that the RGB-CLAHE combination yielded the best performance in two out of the three datasets, demonstrating its effectiveness in enhancing 3D reconstruction across a variety of underwater environments. However, the third dataset, the Mermaid dataset, showed different results, where the unprocessed images produced the best outcome. This discrepancy suggests that the effectiveness of enhancement methods is highly dependent on the specific characteristics of each dataset. Factors such as depth, object count, and scene complexity can influence the performance of enhancement techniques, highlighting the need for a tailored approach. Thus, it is crucial to evaluate which enhancement method is most suited to the characteristics of each dataset to optimize the reconstruction quality.

Table 1. 3D reconstruction results for each enhancement method across datasets.

| Method | Dataset | RP | DF | RF |
|---|---|---|---|---|
| Unprocessed | A | 762,431 | 14,563 | 6,156 |
| CLAHE | A | 836,012 | 17,321 | 7,033 |
| RGHS | A | 691,507 | 11,977 | 5,039 |
| **RGB–CLAHE** | **A** | **846,060** | **18,149** | **7,535** |
| Unprocessed | B | 435,918 | 12,290 | 5,883 |
| CLAHE | B | 446,378 | 12,566 | 5,941 |
| RGHS | B | 405,403 | 11,401 | 5,416 |
| **RGB–CLAHE** | **B** | **469,433** | **13,240** | **6,498** |
| **Unprocessed** | **C** | **264,790** | **13,556** | **2,991** |
| CLAHE | C | 235,625 | 12,581 | 2,716 |
| RGHS | C | 225,567 | 12,911 | 2,556 |
| RGB–CLAHE | C | 258,693 | 12,078 | 2,931 |
| Unprocessed | Total | 1,463,139 | 40,409 | 15,030 |
| CLAHE | Total | 1,518,015 | 42,468 | 15,690 |
| RGHS | Total | 1,322,477 | 36,289 | 13,011 |
| **RGB–CLAHE** | **Total** | **1,574,186** | **43,467** | **16,964** |

*Note: RP = Reconstructed Points, DF = Detected Features, RF = Reconstructed Features.*

## 5. Conclusion

In conclusion, this study evaluated the performance of various enhancement methods, including CLAHE, RGHS, and fusion of RGB and CLAHE, across three distinct underwater datasets. The results demonstrated that the RGB-CLAHE combination consistently produced the best 3D reconstruction outcomes, significantly improving the number of reconstructed points, detected features, and reconstructed features in Datasets A and B. This combination proved to be particularly effective in scenarios with greater depth, visibility, and a higher number of objects. In contrast, the Mermaid dataset, which had fewer objects and was captured at shallower depths, showed a different trend, where the unprocessed images achieved the best reconstruction results. This highlights the importance of considering dataset-specific characteristics when selecting an enhancement method.

While the RGB-CLAHE method showed promising results overall, the discrepancies observed in Dataset C underscore the need for further exploration into the factors that influence the effectiveness of enhancement techniques. The performance of these methods is highly dependent on various environmental and dataset-specific factors, such as depth, object complexity, and visibility. This paper contributes to this evolving landscape by evaluating how different image enhancement techniques influence the accuracy and completeness of underwater 3D reconstructions, providing valuable insights to inform more effective and adaptable workflows for challenging marine environments.

Furthermore, while this study provided valuable insights into the performance of enhancement methods, the absence of ground truth models for the real-life underwater datasets limited the ability to directly validate the results. To overcome this limitation, future research should aim to establish reliable ground truth datasets for underwater scenes, enabling more accurate evaluations of enhancement techniques. Additionally, further investigation into other enhancement methods and their potential applications in underwater 3D reconstruction will be essential to refine and broaden the scope of available techniques.

Future work should focus on developing adaptive enhancement strategies that can dynamically adjust to the unique characteristics of each dataset. By doing so, it will be possible to optimize the 3D reconstruction process and achieve more reliable results across a broader range of underwater environments. Furthermore, the key factors that determine the most suitable enhancement method for each dataset will be explored and analyzed. Other enhancement methods will also be evaluated to assess their effectiveness in improving 3D reconstruction. By gaining a deeper understanding of these factors and expanding the range of techniques considered, more targeted strategies can be developed to optimize 3D reconstruction quality for various underwater environments.

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