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Optimized 3D reconstruction in nearshore underwater environments: A cost-effective pre-processing strategy for Neural Radiance Fields implementation

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Abstract. Nearshore oceans, teeming with diverse benthic ecosystems, continue to be a focal point for marine research. While 2D visual representations have been the mainstay in this area, the intricate, multi-dimensional nature of the seafloor ecosystems underscores the need for 3D modeling to capture their full essence. This study unveils a novel approach tailored for static image processing and 3D modeling through Neural Radiance Fields (NeRF), with a particular emphasis on the refined instantNGP variant. A meticulously crafted pipeline is employed, centered on neutralizing the visual impediments brought about by the interplay of light and seawater in underwater imaging. This refined pre-processing strategy ensures that images are primed for a seamless transition to NeRF-based 3D reconstruction, all the while conserving computational resources. The refined image processing techniques rectify underwater color discrepancies, notably the prevalent blue-green hue resulting from unique lighting conditions. Moreover, the system's ability to identify and excise seawater boundaries guarantees that the 3D models remain singularly focused on the richness of the seafloor ecosystems. Remarkably, achieving this does not demand vast datasets or exorbitant computational prowess, positioning it as an ideal fit for processing images from nearshore regions. As a more resource-friendly and efficient counterpart to existing methodologies, this study furnishes marine ecologists with a powerful instrument for RGB-centric 3D renderings of nearshore terrains. Nonetheless, for broader applicability in diverse marine settings, fusing this approach with neural networks could prove invaluable.

Keywords: Underwater Image Enhancement, NeRF-based 3D Reconstruction, Seawater Detection.

1. Introduction

The world's oceans, in their vast and intricate expanse, remain a forefront of scientific exploration, with a special focus on the study of benthic organisms and ecosystems in nearshore regions [1]. Although underwater imaging tools have made strides in capturing these marine wonders, the predominant reliance on 2D visual representations falls short of encapsulating the multidimensional complexity of the seafloor, teeming with diverse lifeforms and geological formations. Recognizing the limitations of 2D images, especially in representing vibrant nearshore environments with their unique challenges such as structured light modeling complexities and the shortcomings of sonar modeling [2, 3], this research

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pioneers a transformative approach. Leveraging the capabilities of Neural Radiance Fields [4], a novel method is introduced that deftly processes static images for precise 3D modeling, with the added benefit of being resource-efficient. Beyond merely academic fascination, this innovative technique holds immense potential for marine ecologists, especially those immersed in benthic ecology. By offering a more holistic, RGB-based 3D perspective of the underwater realm, this research not only augments marine ecological methodologies but also offers valuable insights that can influence conservation strategies, heralding a new era in understanding and exploring the mysteries of the nearshore marine environment.

2. Background and Related Work

The dataset utilized in this research was sourced from the Institute for Advanced Study at Shenzhen University and predominantly features high-resolution underwater imagery and video footage. These visual assets were captured at depths ranging from 1 to 3 meters off the Saigon coastline. The dataset is particularly rich in visual data concerning corals and geological formations, providing a fertile ground for in-depth analysis. Prior to its application in advanced computational tasks, the dataset underwent a series of rigorous pre-processing procedures, including noise reduction, color normalization, and video frame selection. All data collection efforts were conducted in strict accordance with ethical guidelines pertaining to environmental conservation. The dataset is currently managed by the Institute for Advanced Study and is available for access upon request, subject to the institute's data-sharing protocols.

2.1. Background

Underwater environments offer a unique vista that remains largely unexplored. The deep seas and oceans, with diverse terrains and marine life, hold invaluable information essential for fields ranging from marine biology to geology. Accurate mapping and visualization of these environments are pivotal for further scientific discoveries and advancements.

While satellite imaging and sonar technologies have made strides in underwater mapping, visual-based 3D reconstructions provide a richer, more detailed representation. These reconstructions rely heavily on high-quality input images. However, underwater imaging is fraught with challenges. Water absorbs and scatters light, leading to images plagued with non-uniform lighting, low contrast, and color cast, among other issues.

2.1.1. NeRF, InstantNGP, and Reconstruction. Neural Radiance Fields has established itself as a pivotal method for 3D scene reconstruction from 2D images. Instead of relying on traditional depth maps or voxel grids, NeRF uses a neural network to represent a continuous volumetric scene function. Its performance and adaptability in diverse environments have been emphasized in prior works, but its practicality in underwater settings has been less explored.

Building on the foundational principles of NeRF, the introduction of Instant Neural Graphics Primitives (InstantNGP) marks a notable advancement in the field of 3D reconstruction [5]. InstantNGP streamlines the reconstruction process, enabling near real-time 3D visualization. This accelerated performance is achieved by optimizing the underlying neural structures and leveraging more efficient rendering techniques. Given the time-sensitive nature of many underwater exploration tasks, the adoption of InstantNGP offers potential benefits in terms of rendering speed without compromising on the quality of the reconstruction. The current research aims to tailor and optimizing the capabilities of InstantNGP for underwater environments, exploring its nuances and potential advantages in subaqueous 3D modeling.

2.1.2. Machine Learning-Based Segmentation. Image segmentation in underwater environments poses unique challenges, primarily due to the scattering and absorption of light rays by water and suspended particles. A prevalent methodology to address this problem is based on machine learning techniques [6, 7], which have shown significant capability in segmenting distinct objects submerged in water. Notably, recent efforts in this domain have largely gravitated towards segmenting marine life, often sidestepping the intricacies of the underwater terrain or seabed. While these methods have proven effective in many scenarios, they may have limitation on critical details pertaining to landforms.

2.1.3. Underwater image process. The realm of underwater image enhancement has seen considerable advancements in recent years. A distinctive method hinged on a conditional generative adversarial network (cGAN) was employed for real-time image betterment. This approach critically assessed perceptual image quality across various metrics, and to support this, introduced the large-scale EUVP dataset of underwater images. Notably, these enhanced images showed improved compatibility with standard underwater object detection models [8]. Another study explored adaptive histogram equalization, introducing regional histogram equalization for real-time enhancement, implemented using the Field Programmable Gate Array (FPGA) [9, 10]. Dehazing in underwater images, a challenge due to the pronounced effects of light scattering in turbid waters, was addressed using an algorithm that estimated scene depth by leveraging the differential attenuation across image color channels [11].

3. System Design and Implementation 20% - 30%

3.1. Methodology for Underwater Image Color Enhancement

In addressing the challenges of underwater imaging, particularly the non-uniform illumination and degraded contrast, a three-fold approach was adopted: Histogram Stretching, Color Balancing, and Contrast Limited Apaptive Histogram Equalization (CLAHE).

3.1.1. Histogram Stretching. To alleviate the issues of light absorption and scattering, histogram stretching was implemented on individual RGB channels of the image. The histogram of each channel was linearly transformed such that the minimum and maximum intensity values present were mapped to 0 and 255, respectively. For this process, pixels with zero intensity were ignored to ensure that only meaningful intensities were used to determine the stretching limits. This technique amplifies the color contrast, allowing for a clearer differentiation of features within the underwater environment.

3.1.2. Color Balancing. After stretching, the imgaes often displayed a color cast, particularly due to the preferential absorption and scattering of specific wavelengths underwater. To tackle this, the mean of each channel (R, G, B) was computed and compared with the global mean (for all channels). Each channel was then adjusted to match the global mean, ensuring that the final image was free from color bias. This adjustment balanced the color distribution and minimized the inherent blue or green dominance common in underwater images.

3.1.3. Contrast Limited Adaptive Histogram Equalization (CLAHE). While histogram stretching enhanced the global contrast, it sometimes left local regions of the image under-enhanced. To address this, CLAHE was employed to improve local contrasts. Unlike traditional histogram equalization, CLAHE operates on smaller, overlapping regions of the image, ensuring that the histogram of each tile is equalized independently. This method prevents over-amplification of contrasts and reduces noise. For this application, tiles of size 8 x 8 were used, and a clip limit of 1.0 ensured that the equalization did not produce overly contrasted images.

To facilitate the processing of multiple images, an automation routine was implemented, allowing the enhancement of entire folders of images sequentially.

3.2. Seawater Border Detection for Enhanced 3D Reconstruciton

For precise seabed 3D reconstruction using NeRf, it is imperative to distinguish between the seabed landforms and the overlaying seawater, which manifests as a progressively dominant blue shade in images. Consequently, NeRF may mistakenly reconstruct the seawater as an integral component of the seabed model. To counteract this effect, a methodology was developed to detect the border between the seabed landforms and the seawater.

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3.2.1. Hue-based Image Detection. The color bounds for the seawater were dynamically calculated based on the image's height and the previously computed mean hue value. The lower bound was defined by halving the mean value, while the upper bound was set at a predefined maximum hue value, specifically tailored for blue tones typical of seawater.

3.2.2. Region of Interest (ROI) Definition. To avoid erroneous detections and enhance computational efficiency, only the top half of the image, where the seawater's presence is most evident, was considered as the Region of Interest (ROI).

3.2.3. Seawater Masking. Within the defined ROI, a mask was created to isolate the pixels that fell within the seawater color bounds. Contour detection was applied to this mask to identify and filter out smaller noise areas, ensuring only significant blue regions were kept. To further refine the detection, only contours that met a minimum area threshold and touched the top edge of the ROI were preserved.

3.2.4. Post-processing and Smoothing. Post the primary detection, contours were merged, and morphological operations were applied to smooth and close gaps in the detected regions. A closing operation using a rectangular kernel efficiently filled small holes and connected nearby contours. The resultant mask was then applied to the original image, blackening the detected seawater regions.

3.2.5. Batch Image Processing. An automation pipeline was designed to process multiple images. Each image from the source was loaded, the mean hue value was calculated, and subsequent seawater border detection was carried out.

By identifying and segmenting out the seawater regions, the images were made more suitable for seabed 3D reconstruction with NeRF, ensuring that the resulting model depicted the seabed landforms with increased fidelity.

3.3. Results

3.3.1. Underwater Image Color Enhancement. Qualitative Evaluation.

Visual Enhancement: A series of image pairs, each juxtaposing the original with the enhanced counterpart, showcased the transformation engendered by the proposed techniques. It was discernible that the pervasive blue-green tint in the original images was remarkably alleviated in the enhanced versions, paving the way for a more natural color representation. As shown in Figure 1.

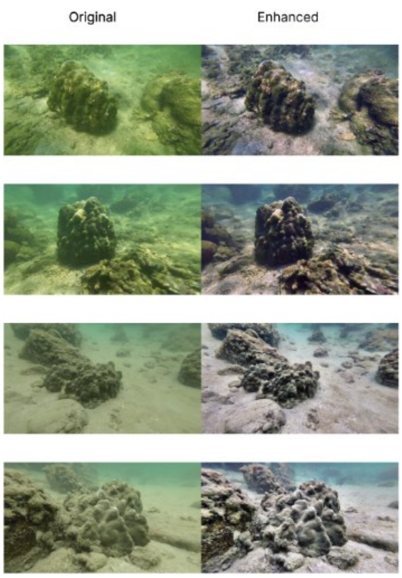

Figure 1. Original vs. Enhanced diagram (Photo/Picture credit: Original).

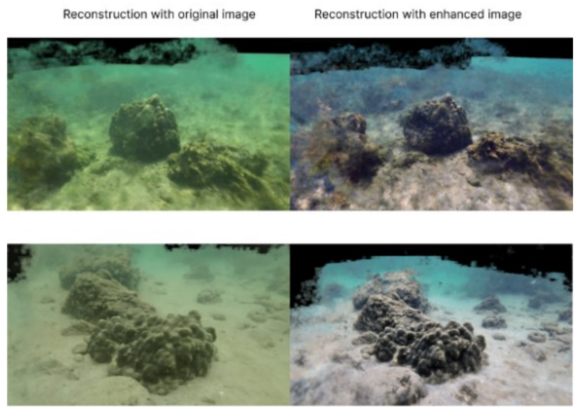

Figure 2. 3D reconstruction based on original / enhanced images (Photo/Picture credit: Original).

Beyond color rectification, a notable enhancement in the visibility of submerged features was observed. Details, previously obfuscated due to unfavorable lighting conditions, were now discernible, indicating the effectiveness of the methodology in mitigating scattering effects and improving image clarity. As shown in Figure 2. Histogram Analysis: In the evaluation of the image enhancement methodology, the histograms of both the original and enhanced images were analyzed. The histograms for each BGR channel of the original image exhibited a pronounced drop, with the green and red channels falling to zero at an intensity of 200 and the blue channel even earlier at 150. This indicates an absence of higher intensities, confirming the visual observation of subdued brightness and potential loss of details in the brighter regions, a common trait in underwater imagery due to selective color absorption. In contrast, the histograms of the enhanced images present a more continuous distribution, stretching further along the intensity spectrum. This behavior signifies the successful restoration of the suppressed pixel intensities, resulting from the applied enhancement techniques. As shown in Figure 3.

Figure 3. Original vs. Enhanced image histogram subjects (Photo/Picture credit: Original).

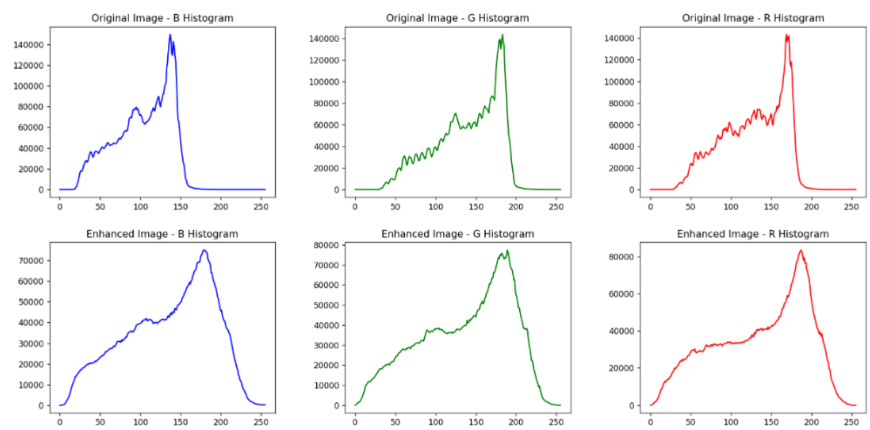

Figure 4. Experimental results (Photo/Picture credit: Original).

Border Detection (Seawater vs. Seabed): In the endeavor to enhance the accuracy of seabed 3D reconstruction using InstantNGP, an essential step involves detecting and isolating the boundary between the seawater and the seabed. The water, especially seawater, presents a significant challenge as it tends to impose a blue tint on photographs due to its light scattering properties. When reconstructing a 3D model, this tint can lead to erroneous inclusion of the water as an actual instance in the output model. As shown in Figure 4. Contour Analysis: On applying the proposed border detection algorithm, contour maps were generated delineating the regions of seawater from the seabed. The methodology employed hue-based detection targeting the characteristic color of the seawater. The resultant contours were smooth, indicating an acceptable border establishment between the seawater and seabed regions.

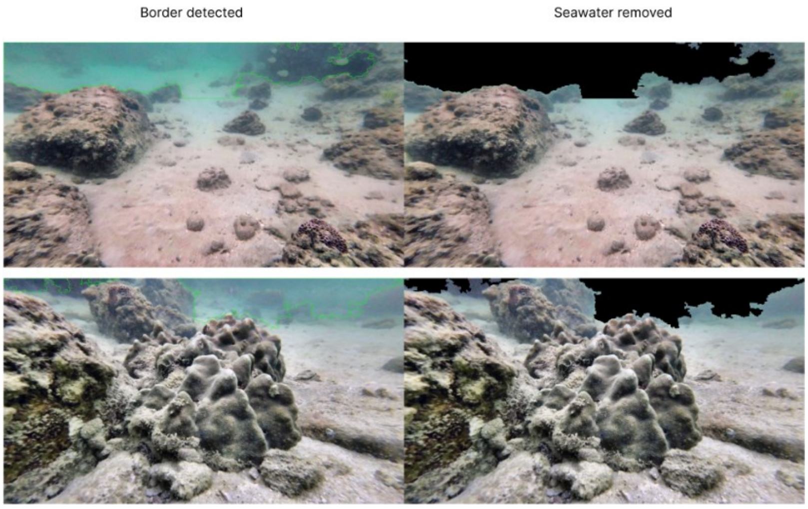

Figure 5. Border detection examples (Photo/Picture credit: Original).

Following the enhanced detection, preliminary evaluations of 3D reconstructions using NeRF were conducted. It was observed that by effectively mitigating the seawater influence in the input images, the reconstructed 3D models exhibited significantly fewer water instances. As shown in Figure 5.

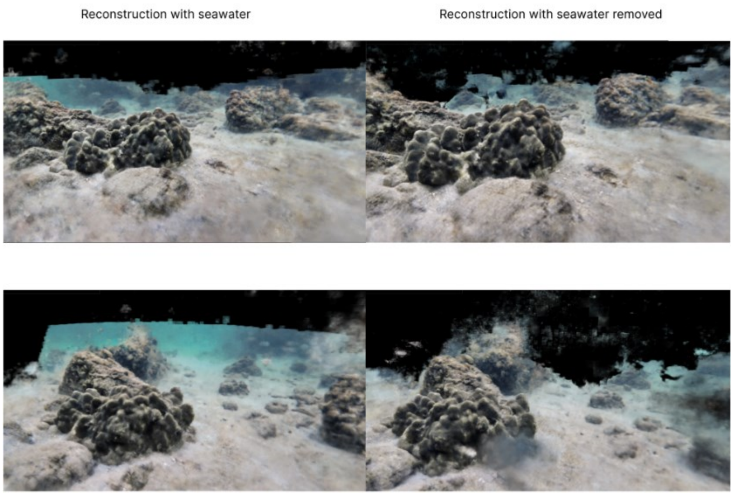

Figure 6. 3D reconstruction with seawater removed (Photo/Picture credit: Original).

One of the distinctive benefits of this pipeline is its inherent computational efficiency. Unlike deep learning-based approaches, which often require extensive computational resources an training time, this pipeline operates a lower level of image processing, thus necessitating fewer computational resources.

As shown in the figure 6. This makes the approach more accessible, especially in settings where high-end computational capabilities are a constraint. Furthermore, a significant advantage of this pipeline is the absence of a dependency on training datasets. Acquiring data, particularly for specific scenarios like near coast underwater environments, can be challenging. In contrast, the developed pipeline can be applied directly to new underwater images without the need for prior training or dataset availability.

4. Challenges and Limitations

While the proposed methodology offers several advantages, there are also challenges and limitations inherent to this approach:

4.1. Limited Generalization Capability

One of the primary challenges is the pipeline's specificity to the 1–3-meter foreshore area. This focus makes its application in broader underwater settings questionable. While the current process can handle certain coastal environments efficiently, its performance may be compromised in diverse underwater conditions.

4.2. Dynamic Seawater Boundary Detection

Accurately detecting and handling the variable nature of seawater across images remains a challenge. The appearance and effects of seawater in imagery are contingent on the scene's distance from the camera due to light attenuation over distance. The method would benefit from a more dynamic algorithm that understands the relationship between hue attenuation and distance, optimizing boundary detection accordingly.

4.3. Geographical Limitations

The method's design assumes a specific orientation of seawater – tapering from top to bottom within the frame, owing to its focus on offshore seabed modeling. This orientation may not hold true for various marine regions. Incorporating more adaptable techniques, potentially involving deep learning networks, could assist in identifying the modeling seawater components across different marine settings.

5. Conclusion

This research presents a tailored framework addressing the unique challenges of underwater imaging, especially in nearshore regions. By prioritizing advanced pre-processing techniques, the system effectively counteracts issues like light interference and the effects of seawater, paving the way for the instantNGP-based NeRF 3D reconstructions. The resulting visualizations offer a more precise depiction of near-coast aquatic terrains, serving as a crucial asset for marine ecologists. Despite its cost-effectiveness and computational efficiency, the model's specificity to particular marine settings highlights the necessity for adaptability in more diverse environments. For further improvement, there's potential in integrating neural networks for refined detection, which, coupled with foundational methods, might address intricate issues, such as evaluating regions impacted by coral bleaching. This combination could broaden the framework's adaptability across multiple marine settings. Another promising avenue is the incorporation of this pipeline into micro Autonomous Underwater Vehicles, potentially facilitating real-time reconstructions of underwater landscapes. Such enhancements could empower AUVs to autonomously survey coastal areas, collecting vital data and contributing significantly to the conservation of these essential ecosystems.

References

[1] De Juan, S., Bremner, J., Hewitt, J., Törnroos, A., Mangano, M. C., Thrush, S., & Hinz, H. (2022). Biological traits approaches in benthic marine ecology: Dead ends and new paths. Ecology and Evolution, https://doi.org/10.1002/ece3.9001.

[2] Zhao, J., Cheng, Y., Cai, G., Feng, C., Liao, L., & Xu, B. (2022). Correction model of linear structured light sensor in underwater environment. Optics and Lasers in Engineering. https://doi.org/10.1016/j.optlaseng.2022.107013.

[3] Kwon, S., Park, J., & Kim, J. (2017). 3D reconstruction of underwater objects using a wide-beam imaging sonar. 2017 IEEE Underwater Technology (UT) (pp. 1-4). Busan, Korea (South). https://doi.org/10.1109/UT.2017.7890306.

[4] Mildenhall, B., Srinivasan, P. P., Tancik, M., Barron, J. T., Ramamoorthi, R., & Ng, R. (2020). NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. arXiv. https://doi.org/10.48550/arXiv.2003.08934.

[5] Müller, T., Evans, A., Schied, C., & Keller, A. (2022). Instant Neural Graphics Primitives with a Multiresolution Hash Encoding. arXiv. https: //doi.org/ 10. 1145/ 3528223. 3530127.

[6] Sarma, K., & Vigneshwaran, P. (2022). Underwater Image Enhancement Using Deep Learning. In J.IZ. Chen, J.M.R.S. Tavares, A.M. Iliyasu, & KL. Du (Eds.), Second International Conference on Image Processing and Capsule Networks. ICIPCN 2021. Lecture Notes in Networks and Systems, vol 300. Springer, Cham. https://doi-org.proxy.lib.umich.edu/10.1007/978-3-030-84760-9_38.

[7] Venkatramanan Sethuraman, A., Ramanagopal, M. S., & Skinner, K. A. (2022). WaterNeRF: Neural Radiance Fields for Underwater Scenes. arXiv. https: // doi. org/ 10. 48550/ arXiv.2209.13091.

[8] Islam, Md J., Xia, Y., & Sattar, J. (2020). Fast Underwater Image Enhancement for Improved Visual Perception. arXiv. https://doi.org/10.48550/arXiv.1903.09766.

[9] Alex, R. S. M., Deepa, S., & Supriya, M. H. (2016). Underwater image enhancement using CLAHE in a reconfigurable platform. OCEANS 2016 MTS/IEEE Monterey (pp. 1-5). Monterey, CA, USA. https://doi.org/10.1109/OCEANS.2016.7761194.

[10] Pizer, S. M., Amburn, E. P., Austin, J. D., Cromartie, R., Geselowitz, A., Greer, T., ter Haar Romeny, B., Zimmerman, J. B., & Zuiderveld, K. (1987). Adaptive histogram equalization and its variations. Computer Vision, Graphics, and Image Processing, 39(3), 355–368.

[11] Carlevaris-Bianco, N., Mohan, A., & Eustice, R.. M. (2010). Initial results in underwater single image dehazing. OCEANS 2010 MTS/IEEE SEATTLE (pp. 1-8). Seattle, WA, USA.