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ADVANCING UNDERWATER IMAGE ENHANCEMENT: NON-REFERENCE EVALUATION WITH A NEW DATASET

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ABSTRACT: The research of marine ecology, marine resources, and marine environment monitoring relies heavily on underwater photographs because they provide a crucial view of the underwater world. One kind of degradation that underwater photographs undergo is color distortion, which is brought about by the absorption and dispersion of light. Because of this deterioration, they become far less effective in subsequent uses such object identification, monitoring, and recognition. Therefore, improving visual information and restoring image quality are the strategies for underwater image enhancement. Augmentation tactics based on images, physics models, deep learning, and other methodologies will be introduced in this work. At the same time, we take a look at relevant measures for evaluating datasets and photos taken underwater. Providing a thorough evaluation of the present and future of underwater image enhancement research and its possible influence on advancements in underwater vision systems is our principal goal.

Keywords **-**Underwater Image Enhancement, Underwater Image Dataset, Quality Evaluation Metrics.

1. INTRODUCTION

Underwater imaging technology has recently garnered significant interest from a variety of industries, such as ocean exploration, underwater archaeology, marine biology, and underwater robotics, due to its numerous applications. Nevertheless, the inherently challenging nature of underwater photography is exacerbated by the unique optical properties of water, which include light absorption, scattering, and attenuation. The color distortion, low contrast, and indistinct features that result from this degradation can significantly impede subsequent picture analysis and interpretation tasks.

In order to mitigate these challenges and improve the visual quality of underwater photographs, numerous underwater picture restoration techniques have been devised. These technologies are designed to mitigate the effects of light attenuation, enhance contrast, correct color distortion, and sharpen picture features in underwater applications that rely on image-based analysis and decision-making. The objective of this endeavor is to conduct a comprehensive examination of the current methods for enhancing underwater photographs.

Our classification system categorizes these methods into three categories: deep learning, physical models, and image-based. The categorization approach is illustrated in Figure 1. Image-based methods enhance contrast, refine edges, and alter colors without directly imitating the underwater photography process by modifying pixel values. Physical model-based solutions utilize mathematical models to elucidate the manner in which light traverses water and the extent to which it is attenuated in order to reverse these effects and restore image quality. In recent years, deep learning-based methods for underwater picture enhancement have achieved exceptional results. These methods learn complex mappings from low-quality to high-quality underwater photographs.

Databases of underwater images are indispensable when it comes to developing and evaluating methods to enhance underwater photography. The publicly available underwater image datasets presented in this work have been extensively utilized by the research community. These datasets are ideal for the training and refining of algorithms that enhance underwater images due to their comprehensive coverage of a wide range of underwater environments and imaging scenarios. Examining the quality of the enhanced underwater images is one of the most critical stages in evaluating the efficacy of various enhancement methods. This research examines a variety of parameters, such as referenced and non-referenced measures, in order to statistically evaluate the visual quality and accuracy of underwater photo enhancements.

By employing these procedures, we can objectively assess various enhancement strategies and construct superior algorithms. This investigation offers a comprehensive examination of underwater picture datasets, underwater picture enhancement methodologies, and criteria for assessing the quality of underwater images. The purpose of this paper is to provide researchers and practitioners with a comprehensive understanding of the current state of underwater imaging by integrating data from these three disciplines and proposing potential areas for further investigation. Our goal with this assessment is to facilitate the development of more advanced underwater photography and its numerous practical applications.

2. LITERATURE SURVEY

Sahu, N., & Jena, S. (2023). This investigation investigates the most recent advancements in underwater image enhancement techniques, with a particular emphasis on the primary challenges posed by dispersion, light absorption, and color distortion. The authors conduct a comprehensive analysis of the advantages and disadvantages of development strategies by categorizing them into three categories: physics-based, learning-based, and hybrid approaches. Machine learning is essential for the restoration of lost image characteristics and the enhancement of visual clarity. Case studies demonstrate that these methodologies have been implemented in various disciplines, including oceanography, underwater robotics, and marine biology. Future research is investigating real-time processing and AI integration, among other things, to address scaling issues and address the gaps.

Mishra, A., & Reddy, P. (2023). This research examines the application of deep learning techniques for the restoration of underwater images, with a particular emphasis on generative adversarial networks (GANs) and convolutional neural networks (CNNs). Underwater performance optimization strategies, loss functions, and datasets are the primary focus of the investigation. A novel GAN model is employed to enhance underwater photos by minimizing local and global aberrations. In comparison to other learning-based and traditional approaches, the writers exhibit significant improvements in clarity and color balance. The article also discusses potential solutions, including semi-supervised learning, as well as drawbacks, including the necessity of processing resources and large labeled datasets.

Kumar, P., & Singh, A. (2023). The primary objective of this investigation is to enhance underwater photographs by establishing generative adversarial networks (GANs). The authors develop a system that employs GANs to enhance texture details and minimize color distortion. In order to demonstrate that GANs are more effective at preserving natural colors and removing anomalies, we compare them to conventional methods. The research employs a diverse array of underwater information to guarantee that the model can withstand a variety of water types. Our objective is to improve generalization by addressing concerns regarding overfitting and computational efficiency, as well as by proposing methods for integrating physics-based priors into GAN frameworks.

Chen, J., & Lee, C. (2023). The research extensively examines underwater image enhancement techniques, examining both conventional and cutting-edge computer-based methods. Histogram equalization, wavelet transform, and deep learning-based models are among the models that fall under this category. The authors test these methods in a variety of underwater environments, such as deep-sea and turbid environments, to guarantee their functionality. Several preparatory methods are described, such as denoising and edge detection. The review's conclusion addresses the importance of uniform evaluation metrics for benchmarking and new areas, such as explainable AI in underwater imaging.

Patel, R., & Shah, M. (2023). This research compares and contrasts data-driven and physics-based methodologies for the enhancement of underwater images. The Structural Similarity Index (SSIM) and the Peak Signal-to-Noise Ratio (PSNR) are two metrics that are employed to assess the algorithms' efficacy. We address real-world applications, such as coral reef monitoring and underwater archaeology. The research emphasizes the primary deficiencies of the existing methodologies, including their excessive dependence on specific datasets and their computational complexity. In order to enhance results, it is recommended to implement hybrid methodologies that integrate traditional image processing techniques with deep learning.

Smith, L., & Alami, M. (2022). This paper introduces a real-time underwater image enhancement system that is based on machine learning. The authors introduce a pipeline that integrates feature extraction, augmentation, and image preprocessing by employing lightweight neural networks. In comparison to conventional methodologies, there are substantial advantages in terms of computational efficiency and clarity. In order to emphasize the system's utility, various real-time deployment scenarios, including autonomous underwater vehicles (AUVs), are examined. The discussion includes future endeavors to optimize models for embedded systems, as well as concerns regarding hardware integration and energy efficiency.

Zhang, X., & Huang, L. (2022). Among other topics, the authors address wavelength-dependent light attenuation and concentrate on color correction techniques that can enhance underwater photography. We introduce a novel method for color restoration that integrates perceptual optimization with statistical methods. The algorithm's ability to reduce visual artifacts while preserving the integrity of natural colors is demonstrated through case studies. The research evaluates the efficacy of the method and proposes a framework for adaptive color correction that is contingent upon water conditions, utilizing current enhancement pipelines as a reference.

Li, H., & Wang, P. (2022). This survey provides a comprehensive overview of underwater image enhancement technologies, with a particular emphasis on real-time applications that employ IoT sensors. The authors evaluate each technique and assign a ranking based on its advantages and disadvantages: optical, computational, and hybrid. The value of edge and fog computing for latency reduction is underscored by the discussion of advancements in these disciplines for use in underwater settings. We not only discuss emerging technologies, such as 5G-enabled underwater networks, but we also propose methods to enhance the scalability and interoperability of underwater photography systems.

Ghosh, A., & Roy, K. (2021). This research examines the potential of convolutional neural networks (CNNs) to enhance underwater photographs by optimizing layers and extracting features. The novel architectural design of the authors was intended to address the challenges associated with underwater imaging, such as turbulence and inadequate illumination. The experimental results demonstrate substantial improvements in texture retention and image quality. The article also explores the potential of transfer learning to enhance training efficiency and reduce the need for extensive datasets. An emphasis is placed on its prospective applications in marine research and underwater surveillance.

Rahman, M., & Khan, S. (2021). The authors provide a comprehensive examination of underwater picture enhancement technologies, with an emphasis on algorithmic advancements between 2015 and 2021. Some of the methods that are critically evaluated include learned models, dark channel priors, and Retinex-based enhancement. This section addresses a variety of challenges, including hardware limitations and computational costs, that surround underwater imaging. The research recommends the implementation of a hybrid architecture that integrates traditional image processing with deep learning to enhance performance. Opportunities for additional research include the development of algorithms that are adaptable to unpredictable circumstances and real-time solutions.

Choudhary, D., & Verma, T. (2021). In this comprehensive investigation, the methods for enhancing underwater photographs are classified into three primary categories: color correction, noise reduction, and contrast enhancement. The authors provide case studies to illustrate how each approach was implemented in the real world, while also evaluating its advantages and disadvantages. The emphasis is on the utilization of conventional metrics to evaluate performance. The paper suggests that synthetic data and cross-domain learning are two potential solutions to the issues that have been identified by the current state of research, such as the limited diversity of datasets.

Zhou, Y., & Xu, B. (2020). This investigation explores the most recent advancements in computational and learning-based methods to enhance underwater images. The authors investigate the impact of environmental factors on picture quality and offer a taxonomy for improving strategies. We examine the challenges associated with achieving scalability and real-time performance, as well as potential solutions, such as hardware acceleration and edge computing. The potential for the integration of artificial intelligence into underwater photography is acknowledged.

Ahmed, M., & Hassan, R. (2020). The authors analyze the challenges and potential solutions for underwater image enhancement by concentrating on ambient variability, sensor limitations, and processing costs. A hybrid strategy that integrates data-driven approaches with optical modeling is proposed as a component of the investigation into advancements in image reconstruction methodologies. We emphasize applications in the military, marine biology, and underwater exploration, and concentrate on real-time implementation challenges.

Kumar, S., & Gupta, N. (2020). This investigation concentrates on the optimization of underwater photographs through histogram equalization, wavelet modifications, and machine learning. A novel approach that integrates wavelet analysis with CNNs is employed to exhibit enhanced color and texture balance. The challenges associated with adapting traditional methods for water use are elaborated upon, and recommendations for hybrid and adaptable methods are provided.

Singh, R., & Sharma, A. (2020). Convolutional neural networks (CNNs) and generative adversarial networks (GANs) are the primary focus of this deep learning approach inquiry for the purpose of enhancing underwater images. In order to address concerns such as color aberration and dithering, the authors propose a CNN design that incorporates numerous scales. Marine research and underwater monitoring are among the practical applications that are illustrated. The research emphasizes computational costs and dataset availability, and it also provides recommendations for future research.

3. UNDERWATER IMAGE ENHANCEMENT DATASETS

A large amount of underwater image data is necessary to train and refine underwater image enhancement algorithms. The model's underwater picture dataset should be examined throughout training and testing to ensure that there is enough underwater image data, as well as the depth of information and variety of underwater situations. We provide a varied range of underwater picture datasets, including the synthetic and paired underwater image datasets, the unpaired real world dataset RUIE, and the paired real world datasets UIEB, UFO, and EUVP.

These datasets include a wide range of degradation kinds as well as rich image information, and they all contain a large number of actual or fake underwater photographs from a variety of domains and imaging equipment. The majority of underwater picture improvement processes contain relevant reference shots or images that have been modified by specialist underwater image enhancement algorithms to allow for comparison and contrast of results. UIEB provides 890 original underwater shots and related high-quality reference photos, as well as 60 problematic underwater photographs.

This dataset contains 60 underwater photographs that are both challenging and visually interesting, displaying a wide variety of underwater landscapes, colors, and content. It also includes extremely high-quality reference photographs. This collection includes a variety of underwater habitats, colors, and visual content. It also includes high-quality reference pictures that may be used to support end-to-end learning and image quality checks. The UFO dataset, which includes 120 test samples and 1500 training samples, is appropriate for detecting remarkable objects, superresolution reconstruction, and underwater image enhancement.

This dataset contains underwater images taken in a variety of water kinds and conditions, and the foreground pixels that were particularly important were carefully selected. The EUVP collection contains 20,000 underwater photos, with 12,000 paired and 8,000 unpaired examples. Various marine locations and visibility circumstances were included in the EUVP dataset, which was acquired with numerous cameras. To account for the wide range of intrinsic changes in the data, some of the photos were taken from publically available YouTube movies.

The RUIE dataset consists of three subsets: UIQS, UCCS, and UHTS. UIQS contains a total of 3,630 underwater images, with 726 in each of the five quality levels. The UCCS subset consists of 300 underwater photos, 100 of which are blue, green, or blue-green distorted. The UHTS subset consists of 300 underwater photos of various marine animals, which are used to evaluate classification and detection systems. The RGB-D NYU-v2 indoor dataset was used to create eleven different image dataset types, with attenuation coefficients representing a variety of water situations.

4. QUALITY EVALUATION METRICS

The assessment of image quality is a significant factor in determining image quality. Quantitative evaluation falls into two categories based on the usage of reference images: reference image quality evaluation and non-reference image quality evaluation.

Reference Evaluation Metrics

Structural Similarity (SSIM) and Peak Signal to Noise Ratio (PSNR) are two commonly used methods for assessing the quality of whole reference pictures. The PSNR value is often used to determine whether the processed image meets the necessary standards. The original photographs differ from those that have been processed with neural networks or other technical ways. To calculate the PSNR for an image of size $m \times n$, follow these steps:

$$PSNR(x,y) = 10 \times \log_{10} \frac{255^2}{E_{MS}} \#(1)$$

$$E_{MS}(x,y) = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{n=0}^{n-1} \|x(i,j) - y(i,j)\|^2 \#(2)$$

Where y is the clear reference image, x is the processed image, and EMS is the mean square error. High PSNR values indicate less visual distortion. SSIM uses three parameters—structural similarity, contrast similarity, and luminance similarity—to assess the degree of resemblance between images. The formula for computing the SSIM is given below:

$$SSIM(x,y) = \left[l(x,y)^{\alpha} \times c(x,y)^{\beta} \times s(x,y)^{\gamma}\right] \#(3)$$

$$l(x,y) = \frac{2\mu_x \mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \#(4)$$

$$c(x,y) = \frac{2\sigma_x \sigma_y + c_2}{\sigma_x^2 \sigma_y^2 + c_2} \#(5)$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x \sigma_y + c_3} \#(6)$$

In this scenario, the processed image is marked by $\boldsymbol{x}$ while the unchanged reference image is represented by $\boldsymbol{y}$. The mean values of $\boldsymbol{x}$ and $\boldsymbol{y}$ are represented by the symbols $\boldsymbol{\mu x}$ and $\boldsymbol{\mu x}$, respectively. The variances of $\boldsymbol{x}$ and $\boldsymbol{y}$ are represented by $\boldsymbol{\sigma x}$ 2 and $\boldsymbol{\sigma y}$ 2.The denominator is avoided from going zero by using constants $\boldsymbol{ci}$ ($\boldsymbol{i}$ = 1, 2, 3). Higher SSIM ratings (range from 0 to 1) imply that the two pictures are more similar. One way to simplify the calculation is to set $\boldsymbol{\alpha} = \boldsymbol{\beta} = \boldsymbol{\gamma} = 1$ and $\boldsymbol{c}2 = 2\boldsymbol{c}3$. The formula for the simplified SSIM is as follows:

$$SSIM(x,y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \#(7)$$

Non-reference Evaluation Metrics

Underwater picture Quality Measurement (UIQM) and Underwater Color Image Quality Evaluation (UCIQE) [60] are two non-reference metrics for assessing picture quality in the absence of reference photographs. UCIQE assesses an image's chroma, saturation, and contrast by analyzing color bias, measuring target local contrast, and exhibiting color fidelity through mean saturation. The formula to calculate the UCIQE is as follows:

$$UCIQE = c_1 \times \sigma_c + c_2 \times c_l + c_3 \times \mu_s \#(8)$$

The standard deviations of chromaticity, luminance contrast, and mean saturation are denoted by Y$\boldsymbol{c}$, $\boldsymbol{cl}$, and $\boldsymbol{\mu s}$, respectively, with weight coefficients of $\boldsymbol{c}1$, $\boldsymbol{c}2$, and $\boldsymbol{c}3$. A higher UCIQE grade suggests that the picture quality is superior. UIQM comprises three components: the Underwater Image Colorfulness Measure (UICM), the Underwater Image Sharpness Measure (UISM), and the Underwater Image Contrast Measure (UIConM).The formula for calculating UIQM is given below:

$$U\quad QM = c_1 \times U_{ICM} + c_2 \times U_{ISM} + c_3 \times U_{IConM} \#(9)$$

The weight coefficients for UICM, UISM, and UIConM are $\boldsymbol{c}1$, $\boldsymbol{c}2$, and $\boldsymbol{c}3$, respectively. A higher UIQM grade indicates that the image quality is superior.

5. CONCLUSION

The current state of the art in underwater picture enhancing technologies is focused on a specific water scene. It is difficult to assess the method's efficacy, universality, and durability, even though there are relevant technologies that can treat a wide range of submerged picture degradation. As a result, it is critical to perform a thorough investigation of the many types of underwater image deterioration and design a universal and reliable underwater image improvement approach for each type. Examine the multi-frequency nature of underwater image data, create underwater image sharpening techniques capable of producing high-quality, improved results, and then advocate for the incorporation of underwater image sharpening technology into marine biological research, underwater survey, and underwater rescue.

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