ReefVista: Deep Learning-Powered Underwater Coral Reef Monitoring

KEERTHANA K
DEPARTMENT OF INFORMATION TECHNOLOGY
SRI SAIRAM ENGINEERING COLLEGE
CHENNAI, TAMIL NADU, INDIA
k.keerthana2030@gmail.com

UTHRA R
DEPARTMENT OF INFORMATION TECHNOLOGY
SRI SAIRAM ENGINEERING COLLEGE
CHENNAI, TAMIL NADU, INDIA
uthraneha80@gmail.com

Dr. SOMA PRATHIBHA
DEPARTMENT OF INFORMATION TECHNOLOGY
SRI SAIRAM ENGINEERING COLLEGE
CHENNAI, TAMIL NADU, INDIA
prathibha.it@sairam.edu.in

Abstract- Coral reefs, characterized by colonies of coral polyps numbering in the hundreds and thousands, hold an exceptional significance. Recently, they've even contributed to the development of medicines with remarkable curative properties. Beyond their ecological importance, coral reefs are prized tourist attractions, driving local economies, and providing invaluable protection against coastal erosion and storm damage. The sustenance, livelihoods, and nutrition of over 500 million individuals worldwide are intricately tied to these remarkable ecosystems. Facilitating their preservation and ensuring their health is the Global Coral Reef Monitoring Network (GCRMN), a collective of enterprises, scientists, and administrators responsible for vigilantly assessing the state of coral reefs across the globe through a network of ten regional nodes. Moreover, the realm of underwater image processing has garnered noteworthy attention due to its pivotal role in marine engineering, oceanography, and the advancement of submarine robotics. While numerous methods have been devised to improve underwater image quality, a substantial proportion has relied upon synthetic datasets or a sparse selection of authentically labeled images for validation. In this paper, we introduce a suite of advanced deep learning-based techniques tailored for the monitoring of coral reefs and the enhancement of underwater imagery. Significantly, these techniques not only augment the quality of the images but also deliver markedly superior results when contrasted with earlier enhancement and restoration methodologies.

Keywords- Coral reef monitoring, image enhancement, Bright channel prior, deep learning

I.INTRODUCTION

The ever-evolving landscape of computer vision and image processing technologies has catalyzed a burgeoning interest in the application of image processing methods to enhance the quality of underwater imagery. This pursuit seeks to cater to the requisites of both human visual interpretation and machine-based recognition. Currently, two primary categories of approaches are employed for the improvement and restoration of underwater images: model-driven enhancement and restoration grounded in physical models.

Conventional methodologies for augmenting underwater image quality encompass techniques like color correction and contrast enhancement algorithms. Notable among these are contrast-enhancing algorithms such as histogram equalization and limited discrepancy histogram equalization. In the realm of color correction, methods like white balance, slate world thesis, and slate edge thesis are frequently employed. Nevertheless, owing to the intricate nature of the aquatic environment and the presence of various adverse factors, such as light dispersion and absorption by water and the deep-sea milieu, coupled with suspended particulate matter, the outcomes achieved via these conventional techniques fall short of catering to the demands of underwater vision.

The journey of light through water causes a decline in its intensity, subsequently resulting in underwater images that manifest with a distinct greenish-blue hue. This coloration occurs due to the substantial attenuation of specific wavelength components, with a more pronounced impact on longer wavelengths compared to their shorter counterparts. At depths of around 4 to 5 meters beneath the water's surface, the images primarily encompass red wavelengths, as longer-wavelength elements in the visible spectrum experience initial attenuation. With increasing depth, the reduction in intensity also engulfs other wavelength components, thereby giving rise to imagery characterized by a restricted field of view, non-uniform illumination, and pronounced artifacts. Consequently, any image captured in this milieu invariably incorporates certain noise elements, leading to a low-contrast appearance with a subdued color spectrum.

II. LITERATURE SURVEY

To address the issues of color degradation, contrast diminishment, and detail blurring observed in underwater images, researchers have devised more intricate and comprehensive techniques for image enhancement. Ghani and his team [1] introduced a method that enhances the low contrast in underwater images by employing a Rayleigh-extension constrained contrast adaptive histogram equalization approach, thus equalizing both the global contrast-enhanced image and the initial contrast-enhanced image. This strategy not only ameliorates overall image quality but also enhances its visual appeal.

In the pursuit of enhancing underwater prints, Li et al. [2] proposed a holistic approach that accounts for multiple factors affecting image quality. Their approach encompasses various techniques, including image dehazing algorithms, color compensation histograms, equalization adjustments for color neutrality, intensity stretching for illumination, and bilateral filtering algorithms. These techniques effectively address issues such as blurriness, color fading, low contrast, and noise in underwater imagery. In contrast, Braik et al. [3] harnessed particle swarm optimization (PSO) as part of a flyspeck mass optimization method to mitigate the influences of light absorption and scattering in underwater images.

Furthermore, Fu et al. [4] introduced a Retinex-based method for enhancing underwater images. Deep learning-based techniques have showcased immense potential in elevating the quality of underwater imagery by learning from extensive datasets. Notably, Perez et al. devised a model utilizing deep learning methods capable of distinguishing between damaged and recovered underwater images. This facet is particularly valuable for identifying areas within an image that require further enhancement or restoration. In sum, these methodologies and algorithms represent substantial strides in enhancing underwater image quality and hold significant promise for applications in realms like ocean exploration, marine biology, and underwater archaeology.

Zhou [5] engineered a multifaceted, conflation-based system intended to augment the aesthetic appeal of underwater prints. It is evident that the domain offers a plethora of methods and techniques to enhance underwater image quality. Researchers are continually delving into novel approaches to tackle the distinctive challenges posed by the underwater environment.

Zhou [8] devised a unique method for simulating realistic low-light blurring degradation. This approach involved a specially curated dataset and the LED-Net network, which achieved simultaneous low-light enhancement and deblurring. Building upon concepts from LED-Net, a modified version of the Zero-DCE network was created, accompanied by a low-light image dataset. The intent was to enhance both low-light quality and alleviate scattering. However, it's important to note that this modified version of the Zero-DCE network is distinct from the original.

This research endeavor [12] aspires to enhance the management and conservation of the marine environment in the Persian Gulf. The primary objective is to identify and assess the damage sustained by marine flora due to various factors, including climate change, water pollution, encompassing oil pollution and urban wastewater, and human activities. The research methodology adopts a convolutional neural network (CNN) for this purpose. It's noteworthy that this undertaking encountered challenges related to the monitoring of coral bleaching.

In scenarios where KinD and Retinex-Net produce the illuminance map and reflectance map individually for image enhancement, a simultaneous input of both the deconstructed illumination map and reflectance map into the restoration network is undertaken. This approach synergistically enhances both the illumination map and the reflectance map, culminating in a restored image that aligns with the original image.

Moreover, the authors draw attention to the conceptualization within KinD, where image degradation induced by low-light conditions is regarded as "pollution" in the image scene's reflectance map. The authors also recommend further exploration of the feasibility of accommodating the degradation stemming from both low-light and scattering as a form of "pollution" linked to image reflectance.

III.METHODOLOGY

3.1 Existing System**

Upon a comprehensive review of the literature, it is evident that many contemporary researchers have not devoted sufficient attention to addressing a multitude of interconnected issues in their work. For instance, a considerable portion of haze removal algorithms does not adequately tackle the problem of noise, and the dark channel prior (DCP) remains relatively underexplored. Furthermore, the aspect of uneven brightness is frequently overlooked, which can compromise the efficacy of haze removal algorithms. Several earlier approaches, including strategies such as excessive contrast enhancement or color saturation, have yielded inconsistent results, introducing variability into the final image coloration.

In the realm of computer vision, the capability to discern objects is of paramount significance for various visual tasks encompassing scene comprehension, image search, object tracking, and print bus-reflection. Object tracking, particularly in the context of monitoring moving objects within video sequences, stands as a pivotal computer vision task with applications spanning intelligent surveillance systems, artificial intelligence, military guidance, safety detection, robot navigation, and medical and natural operations. While significant strides have been made in the development of single-object tracking systems, the complexity escalates when dealing with multiple objects. Tracking becomes increasingly formidable when objects are either partially or entirely occluded, rendering them imperceptible to the human eye due to variations in viewing angles and illumination conditions.

The prevailing object shadowing system, founded upon Multi-Layer Perceptrons (MLPs), is remarkably robust. This robustness is achieved by leveraging the Adaboost strong bracket fashion in tandem with a meticulous selection of distinguishing attributes. To optimize the training of the network model, the approach mirrors the fashion employed for DSSD on ResNet. The primary objective is to enhance sensitivity. The initial enhancement pertains to the substitution of the VGG network, originally utilized in SSD, with ResNet. Additionally, a series of complexity point layers is integrated into the final subcaste of the underlying network.

In the realm of object detection, region proposal methods such as R-CNN have demonstrated noteworthy improvements in performance by curtailing the number of candidate regions necessitating classification. This approach streamlines the detector's focus onto the most promising regions, thereby conserving computational resources that might have been squandered on image areas unlikely to harbor objects. In the context of R-CNN, the selective search methodology is harnessed to generate approximately 2000 region proposals, which are subsequently subjected to classification via a Convolutional Neural Network (CNN). Subsequent works have expanded and refined this methodology, exemplified by Faster R-CNN and Mask R-CNN.

However, it's crucial to acknowledge that R-CNN exhibits certain limitations, particularly in terms of computational efficiency during both training and testing phases. This can impede its real-time applicability. The selective search algorithm, employed for region proposal generation, is time-intensive, and the substantial volume of region proposals exacerbates this issue. Furthermore, the absence of an end-to-end training framework within R-CNN can result in suboptimal region proposals, consequently diminishing the overall system's accuracy.

3.2 Proposed system

Image enhancement techniques are widely employed in the realm of image processing to ameliorate the quality of images suffering from issues related to poor illumination. In our research, we introduce a novel brightness enhancement algorithm founded on the principles of the Bright Channel Prior (BCP), with a specific emphasis on the rectification of gray areas. The BCP model capitalizes on the observation that local image patches frequently contain pixels characterized by remarkably high brightness values, a common occurrence in well-lit images. The adoption of this model empowers us to enhance the quality of images previously afflicted by atmospheric haze.

In our initial image preprocessing step, we incorporate gamma correction, a technique aimed at intensifying the image by a factor defined by gamma. This process accentuates the darker tones to a greater extent than the lighter ones, thereby linearizing the non-linear output of a Cathode Ray Tube (CRT) display, ensuring that the output (Vout) aligns with the input (Vin). Employing a lookup table, we systematically map pixel values within the 0 to 255 range to their respective gamma-modified counterparts. To address visibility issues stemming from atmospheric haze or fog, we turn to Contrast Limited Adaptive Histogram Equalization (CLAHE), a variant of Adaptive Histogram Equalization (AHE). CLAHE mitigates the problem of excessive contrast amplification that can afflict traditional AHE techniques. It achieves this by operating on distinct tiles, non-overlapping sections of the image. These tiles are then harmoniously combined using bilinear interpolation, effectively eliminating artificial boundaries. CLAHE, through the computation of multiple histograms for different regions of the image, effectively redistributes brightness values. This technique excels at enhancing local contrast and edge definition within each region.

Our research is motivated by the overarching goal of identifying and classifying coral reefs, which can be categorized into three primary types: atoll reefs, barrier reefs, and fringing reefs. In the pursuit of this objective, we harness the capabilities of Convolutional Neural Networks (CNNs). CNNs, often referred to as covnets due to their utilization of shared parameters, are highly suited for image analysis. Their intrinsic capacity to manage the high-dimensional data that characterizes images, akin to a cuboid with dimensions representing length, width, height, and RGB channels, makes them an indispensable tool for our research.

Beyond the image enhancement and reef classification aspect, our study also extends to the realm of coral reef mapping. We endeavor to create comprehensive maps that delineate the geographical distribution of coral reefs. These maps can serve as invaluable resources for researchers, conservationists, and marine biologists seeking to monitor, understand, and protect these vital ecosystems. Moreover, it is imperative that our findings and coral reef maps are effectively communicated to relevant stakeholders, particularly the fishing community and fishery departments. Raising awareness about the location and health of coral reefs is essential in ensuring their long-term preservation. By sharing our research outcomes, we aim to empower fishermen and the fishery sector with the knowledge needed to sustainably manage their activities and protect the fragile coral reef ecosystems that play a pivotal role in marine biodiversity and coastal protection.

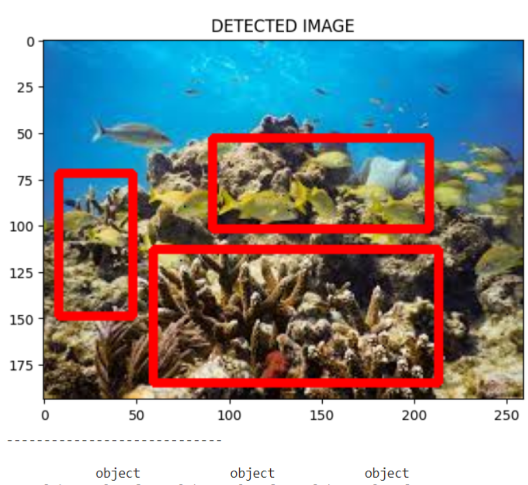
IV. RESULT AND CONCLUSION

In this research, we have introduced an innovative methodology for enhancing individual images, and it revolves around the utilization of the Bright Channel Prior (BCP) technique. To optimize the enhancement process, we have integrated essential preprocessing steps. This involves employing gamma correction to fine-tune the overall brightness of the image, ensuring that it aligns with the desired visual quality. Furthermore, we have harnessed the power of Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance image equalization. Notably, CLAHE works on distinct image tiles, offering a targeted and effective approach to image improvement.

Our image enhancement technique unfolds in three distinct phases. First and foremost, we have introduced a superpixel-based methodology for estimating atmospheric light. This approach is pivotal in enhancing the precision of atmospheric light estimation, a critical factor in image enhancement. The integration of the BCP model plays a central role in this phase, helping us effectively manage the presence of bright spots that frequently plague hazy images, particularly during the transmission estimation stage.

To take our research a step further, we have harnessed the capabilities of Convolutional Neural Networks (CNNs). These advanced neural networks serve as the backbone for our coral reef detection and categorization tasks. We believe that employing CNNs is instrumental in achieving the high-level accuracy and efficiency required for these critical tasks.

As a culmination of our efforts, we emphasize the monitoring of the coral reef ecosystem's health and conditions. This aspect of the research is not only about the present but also holds promise for potential future enhancements. By keeping a vigilant eye on the state of coral reefs, we pave the way for proactive conservation and preservation efforts. Our methodology extends beyond immediate image enhancement, making it a valuable tool for the ongoing protection and understanding of these vital marine ecosystems.



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