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Review of Underwater Image Color Restoration using Artificial Intelligence Techniques

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***Abstract*— Underwater imaging is a key carrier and display of underwater information, which plays a major role in the exploration, exploitation, and usage of marine resources. This review comprehensively examines various AI techniques employed for underwater image color restoration, including deep learning models, convolutional neural networks (CNNs), and image enhancement algorithms. We analyze the strengths, limitations, and advancements of these approaches, providing insights into their effectiveness in different underwater scenarios. The synthesis of AI and underwater imaging holds significant potential for improving the accuracy and reliability of color restoration, thereby enhancing the overall quality of underwater visual data.**

Keywords—Underwater, Image, Color, Restoration, AI.

I. Introduction

Computer vision is an essential tool for a variety of underwater applications, including scientific research, the discovery of resources, and others. However, it has considerable color distortion, which is brought on by the scattering and absorption of light in the water. This is a problem since it makes the color less accurate.

Underwater imaging encounters formidable challenges due to the inherent properties of water, such as light absorption, scattering, and attenuation. These factors contribute to the degradation of image quality, particularly in terms of color fidelity. The need for accurate and vibrant color representation in underwater images is critical for various applications, including marine biology, environmental monitoring, and underwater archaeology. Traditional image processing techniques often fall short in addressing the complexities of underwater color restoration, prompting the exploration of advanced Artificial Intelligence (AI) methods.

In recent years, the integration of AI has emerged as a promising avenue for mitigating the effects of color distortion in underwater images. This review aims to provide a comprehensive overview of the current state of research on underwater image color restoration using AI techniques. We delve into the fundamental challenges posed by the underwater environment, emphasizing the impact on color perception. Subsequently, we explore the diverse range of AI methodologies applied in this context, such as deep learning models and convolutional neural networks (CNNs). The review also assesses the strengths and limitations of these approaches and discusses notable advancements in the field.

Through a systematic analysis of the literature, this review seeks to offer valuable insights into the efficacy of AI-based techniques for underwater image color restoration. By understanding the current landscape of research in this domain, researchers and practitioners can make informed decisions in selecting or developing methodologies that align with the specific requirements of underwater imaging scenarios. The synthesis of AI and underwater imaging not only addresses the challenges posed by color distortion but also opens avenues for further advancements in the broader field of underwater computer vision.

II. LITERATURE SURVEY

J. Lu et al., [1,] estimate the primary parameters of an underwater imaging model to determine the image's true color. First, an encoder neural network is applied to the input picture of an underwater scene in order to extract features from the image. Second, estimates of the direct light transmission map, the backscattered light transmission map, and the veiling light are generated with the use of three separate decoders. Third, in order to enhance the effectiveness of the restoration process, both the loss functions and the training approach have been developed. As is common knowledge, the learning-based strategy would call for the use of a data collection consisting of paired examples for the training phase. In this work, we also present a technique for the production of underwater photographs in order to get the data set that consists of color-distorted images and the ground truth corresponding to those images.

H. Wang et al., [2] This information is essential to the exploration, exploitation, and utilization of marine resources. However, because of the constraints of the objective imaging environment and the equipment that is used in it, the quality of underwater photographs is almost always poor. These images suffer from a variety of degradation phenomena, including low contrast, fuzzy details, and color deviation, all of which severely impede the growth of related disciplines. As a result, academics have been paying a growing amount of attention to the question of how to improve and recover deteriorated underwater photos via the use of post-production algorithms. In recent years, there has been a fast growth of technology associated with deep learning, which has led to significant advancements in the improvement and restoration of underwater images using deep learning. In this paper, we propose an improved MSCNN underwater image defogging method.

G. Ramkumar et al., [3,] The field of digital image processing is expanding on a daily basis thanks to the development of innovative technologies that may support a variety of applications. These applications include robotic endeavors, the establishment of undersea networks, and many more. Due to the flow of light waves that are not in the precise and anticipated range beneath the water level, underwater image processing is regarded to be the most important work in the business of image processing. This is because light waves behave differently when they pass through water. Even while image restoration technology is capable of effectively eliminating the same haze from source photos, the fact that it requires the collection of several images from a single location prevents it from being employed in a system that operates in real time.

S. Wu et al., [4] presented a two-stage underwater enhancement network, which would consist of a preliminary enhancement network and a refinement network respectively. During the first step, it is recommended to create the preliminary enhancement network, which is comprised of both the high-frequency and the low-frequency enhancement networks. The high-frequency component is improved directly by a deep learning network, but the low-frequency enhancement network is based on the underwater imaging, which is an integrated transmission map and background light into a joint component map. The second step of the process involves the refinement network, which is aimed to further improve the color of the underwater picture by taking into consideration the intricacy of underwater photography.

Y. Lu et al., [5,] the goal of this work is to find a way to eliminate speckle noise completely blindly. Through the use of a logarithmic transformation, the multiplicative connection that previously existed between the latent crisp picture and the random noise will first be turned into an additive form. To further enhance the robust generalization provided by DSPN et, the multi-scale mixed loss function has been suggested as a potential solution. The deep blind despeckling network that was presented is capable of both lowering the amount of random noise and maintaining important picture information. Experiments using synthetic data as well as true data have shown that our DSPNet provides higher performance in terms of quantitative assessments and the visual picture quality they produce.

Y. Lin et al., [6] presented network splits the restoration process into two parts—namely, horizontal and vertical distortion restoration—in order to handle both aspects of the issue. In the initial step of the process, it is suggested to use a model-based network to deal with horizontal distortion. This would be accomplished by directly integrating the underwater physical model into the network. In order to guide the proper estimation of the parameters in the physical model, the attenuation coefficient, which is a feature representation in describing water type information, is first calculated. This helps lead the process. In the second step, in order to address the problem of vertical distortion and reconstruct a clean picture of the undersea environment, we developed a unique attenuation coefficient prior attention block (ACPAB) that can adaptively recalibrate the RGB channel-wise feature maps of an image that is affected by vertical distortion. This allows for the problem to be resolved. Experiments conducted on synthetic datasets as well as photographs taken underwater in the real world reveal that our technique is superior to numerous other state-of-the-art approaches in its ability to successfully combat scattering and absorption.

R. Liu et al.,[7] deep learning strategies for picture dehazing have developed to a more mature stage, grown more trustworthy, and shown excellent performance. Despite this, these techniques are strongly reliant on the data used for training, which limits the scope of their applications. More significantly, both standard learning methods and deep learning techniques neglect a common problem, which is that sounds and artifacts always arise throughout the recovery process. In the learnable framework that we have built for the purpose of picture dehazing, the Hadamard-product-based propagations are formed. In this manner, we are able to eradicate any sounds or artifacts that may be present in the recovery process in order to get the optimum results. After that, due to the generalizability of our HP model, we were able to effectively expand our LHPP in order to resolve issues with low-light image enhancement as well as underwater picture enhancement. In order to validate the efficacy of our methods, a number of analytical studies are carried out. Numerous performance tests on three difficult tasks have unequivocally shown our superiority over a variety of state-of-the-art approaches.

Y. Pei et al., [8,] Deep learning neural networks, particularly Convolutional Neural Networks (CNNs), have helped make considerable strides in recent years in the field of picture categorization. This is similar to the success that has been made in many other areas of computer vision. Image databases like Caltech-256, PASCAL VOCs, and ImageNet are examples of the kind of studies that have been done in this area, and the majority of those efforts concentrated on the classification of highly clear natural photos. However, in many practical applications, the pictures that are collected may have certain degradations that lead to a variety of different types of blurring, noise, and distortions. The influence that such degradations have on the performance of CNN-based image classification is an important and intriguing subject, as is the question of whether or not the elimination of degradations aids CNN-based image classification.

Z. Wang et al., [9] Exploration of the ocean by humans has been growing at a steady rate despite the ongoing depletion of terrestrial resources. Imaging the ocean floor from below is one of the most straightforward ways to get insight into the ocean's interior conditions. Underwater photos, on the other hand, suffer considerable deterioration as a result of the complicated imaging environment of the ocean as well as the light scattering that occurs in the sea, making it impossible to differentiate between effective information. Therefore, improvements need to be made to imaging capabilities underwater. Deep learning has been successfully employed in the area of computer vision, particularly when contrasted with more conventional approaches (such as the histogram equalization method) and modeling methods. The capacity of the convolution model to generalize is essential, along with the acquisition of the training data, since these are the main factors. Both the model-based technique, which will inevitably lead to mistakes due to the need of manually measuring previous data in preparation, and the direct generalization of the neural network, which will also result in the blurring of images. This research presented a double U-Net for the improvement of underwater images that has a high capacity for generalization.

E. Silva et al., [10] The fast expansion of computing and sensor capacity has made it possible to build picture restoration technologies that are applicable to underwater photography. When it comes to robotic vision applications, water presents a significant barrier due to the great degree of absorption it has. A depth map is required for many different applications of underwater robots, and this presents a fundamental challenge. The absence of huge data sets with which to verify the approach or even train a learning-based method is one of the obstacles that must be overcome in order to get monocular depth images of the ocean floor. For the estimate, many techniques have been offered in the state-of-the-art, either based on a physical model or on a deep learning approach.

III. CHALLENGES

The restoration of underwater image color using artificial intelligence techniques is confronted with several challenges, stemming from the unique characteristics of the underwater environment. These challenges significantly impact the accuracy and reliability of color restoration methods. The primary challenges include:

1. **Light Absorption and Scattering:** Water absorbs and scatters light, leading to a reduction in the intensity and altered spectral composition of the light that reaches the underwater scene. This phenomenon causes color distortion and a loss of contrast, making it challenging for AI algorithms to accurately restore the true colors of objects in the image.

2. **Depth-Dependent Illumination:** The attenuation of light is depth-dependent, resulting in variations in illumination conditions with depth. AI models must account for these variations to achieve consistent color restoration across different depths, which require sophisticated algorithms capable of adapting to changing lighting conditions.

3. **Limited Training Data:** Acquiring labeled training data for underwater image color restoration is challenging due to the cost and difficulty associated with collecting accurately annotated underwater image datasets. Limited training data can hinder the generalization capabilities of AI models, making them less effective in real-world underwater scenarios.

4. **Complex Underwater Scenes:** Underwater environments are often characterized by complex scenes with diverse marine life, varying water compositions, and dynamic lighting conditions. AI models need to handle this complexity and diversity to achieve robust and accurate color restoration, requiring a balance between model complexity and generalization ability.

5. **Heterogeneous Water Conditions:** Different water bodies exhibit distinct optical properties, such as varying levels of turbidity and suspended particles. Designing AI models that can adapt to these heterogeneous water conditions and perform effectively across different underwater environments is a significant challenge.

6. **Real-Time Processing:** Many underwater applications, such as underwater robotics and monitoring systems, require real-time image processing. Achieving efficient and real-time color restoration using AI techniques poses a computational challenge, as complex models may have high computational demands that hinder their applicability in real-world, resource-constrained environments.

7. **Evaluation Metrics:** Establishing standardized evaluation metrics for assessing the performance of AI-based color restoration methods in underwater environments is crucial. Current metrics may not fully capture the perceptual quality and fidelity of color-restored images, making it challenging to compare and benchmark different approaches consistently.

IV. CONCLUSION

The fusion of Artificial Intelligence (AI) techniques with the realm of underwater image color restoration holds great promise in addressing the formidable challenges imposed by the unique characteristics of the underwater environment. This review has provided a comprehensive examination of the current state of research in this domain, highlighting the significance of AI methodologies in mitigating issues related to light absorption, scattering, depth-dependent illumination, and complex underwater scenes.

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