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# *A Survey of Underwater Degraded Image Restoration*

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***Abstract.*** Underwater images serve as essential visual data for marine resource exploration, underwater robot operation, and other related fields. Due to light absorption by water, scattering by suspended particles, and refraction distortion caused by imaging devices, usually, there will be degradation problems such as color shift, blurring and low contrast. This study examines the negative effects of these issues on the efficiency of certain visual analysis tasks. We present a detailed survey on rehabilitation approaches for underwater images. We describe the disparate effects of underwater image degradation and summarize their physical causes. Existing image restoration approaches fall into three primary types: (1) physics-based methods, (2) non-physics-based methods, and (3) deep learning-based methods. We also analyze the pros and cons, as well as the integration perspective, of these methods. Additionally, we review the existing underwater image datasets and quality assessment frameworks to present the current state and issues of these methods. This study builds a knowledge base for subsequent works on underwater image restoration, advocating for a faster deployment of the restoration methods for underwater image rehabilitation to a wide range of applications in marine engineering and underwater exploration. This organized systematized literature review is prepared to aid researchers in the future by providing a structured reference framework regarding the restoration of degraded underwater images. We anticipate the implementation of the technologies detailed in this review to further improve the mitigation of underwater obstructions within a lateral distance of the submersible craft and the attire of underwater construction.

***Keywords:*** Underwater images, Underwater degraded image restoration, Deep learning-based methods, underwater detection

## 1. Introduction

Ocean development and use is of great importance to national defence and economic development. Underwater images are an essential means of underwater sensing. They play an important role in various applications such as resource development, environmental monitoring and engineering work. Light is absorbed and scattered in water. This results in widespread degradation of underwater photographs. These problems include extreme color casts, poor contrast, lack of sharpness, and poor illumination. These significantly impact underwater operations and underwater robotics.

For close-range underwater robot operations, vision is superior to sound. Cameras are low in cost, small, responsive, have rich texture and high resolution. These advantages make them ideal for

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precise operations. However, capturing high-quality visual data underwater is a great challenge. First, underwater environments directly affect image quality, such as the high turbidity of water, the lack of intensity and saturation of single tones, and the lack of uniform lighting. Figure 1 shows the 3D Color Distribution Map and the three-channel RGB histogram of underwater images, which illustrates the significant color distortion, low contrast and low brightness of underwater images. For another, the waterproof housing results in image distortion. It introduces deflection of optical paths in multiple media, which also results in pixel distortion.

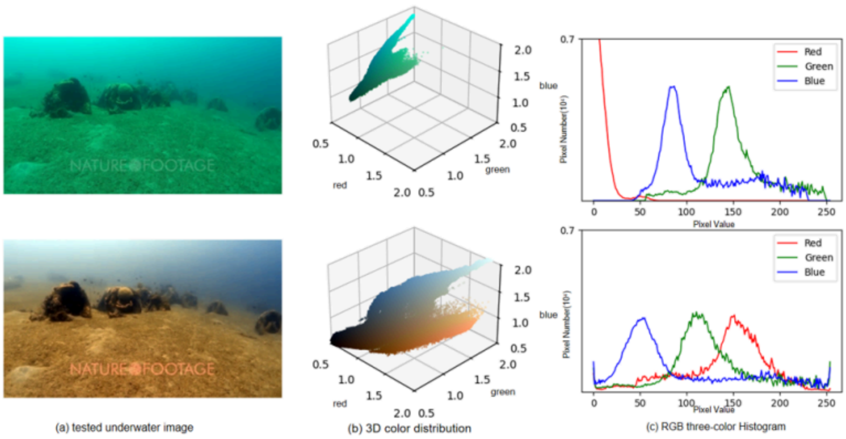


Figure 1. Distribution differences before and after underwater image restoration

For these reasons, we should consider effective methods for restoring underwater images of poor quality. This can enhance the smart perception capability of underwater environments. The existing underwater image restoration approaches can be broadly divided into three types: physical model-based, non-physical model-based and deep learning-based. In general, the current methods still have limitations in various underwater scenarios. This paper aims to resolve this issue by conducting a systematic investigation and integration of underwater image restoration tasks, to offer a thorough review for future work.

## 2. Causes of underwater image degradation

The optical complexity of the underwater environment is the core bottleneck restricting the performance of underwater vision systems. As shown in Fig. 2, two physical effects are the root cause of underwater image degradation: the selective absorption of light by water, and scattering by suspended particles in water.Other factors can also cause severe visual quality issues. These include uneven illumination from artificial light sources and the physical limits of imaging hardware. Typical hardware limits include insufficient sensor dynamic range and lens distortion.All these factors will worsen image noise and cause resolution loss. They ultimately lead to a decline in overall image quality.In summary, the main causes of underwater image degradation can be divided into four varieties: the selective absorption of water, the scattering effect of suspended particulates, uneven illumination from artificial light sources, and the physical constraints of imaging equipment.

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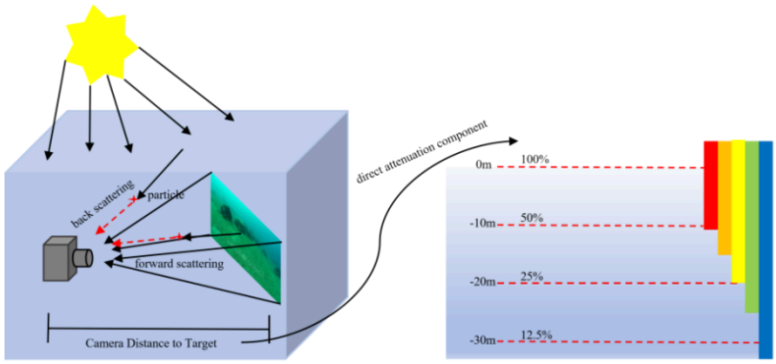


Figure 2. Light attenuation in water and underwater imaging process

## 3. Underwater image restoration methods

### 3.1. Non-physical model-based methods

In recent years, researchers have proposed numerous non-physical model enhancement methods to address the problem of underwater image degradation. These methods do not rely on physical imaging models, but directly improve visual quality through digital image processing techniques. Non-physical model methods address underwater image degradation through multiple complementary technical routes, covering frequency-domain processing, spatial-domain enhancement, colour constancy, fusion-based strategies, filtering and signal processing, and Retinex theory.

Frequency-domain techniques, including low-pass, high-pass, homomorphic filtering and wavelet transform [1], are widely adopted to split and optimize different image feature components. Spatial-domain methods, including histogram-based approaches (AHE, CLAHE), gamma correction, colour constancy adjustment and the grey world assumption, are used to boost contrast and correct colour casts, yet they easily trigger noise amplification and excessive image over-enhancement [2,3]. Colour constancy methods, based on white balance and Retinex-related algorithms, aim to restore true image colours and adaptively optimize uneven illumination, and often need to be combined with other techniques to mitigate local colour distortion [4,5].

Fusion-based methods generate multiple enhanced versions from a single input image, then integrate them through multi-scale or multi-weight strategies. They effectively improve contrast, saturation and texture details, but face challenges in optimal input and weight selection [6,7].

Homomorphic filtering and Laplacian decomposition are two representative methods under the filtering and signal processing category. They achieve excellent results in image noise removal and edge feature preservation [8,9]. Yet they require heavy computing resources, and are very sensitive to parameter choices.Various Retinex-based derived models are widely used in underwater image processing, including Multi-Scale Retinex, its colour restoration variant, variational models and underwater-adapted versions.They excel at addressing uneven illumination and enhancing colour fidelity, but have high computational overhead and strong reliance on proper parameter tuning [10].

Overall, these non-physical model methods have made notable contributions to addressing common underwater image defects (colour distortion, low contrast, blurred details, noise), providing solid technical support for the development of underwater image restoration research.

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### 3.2. Physical model-based methods

Physical model-based methods are used to restore underwater images. The underlying principle is to remove the process of image degradation, with its theory including underwater optical imaging models, polarisation, and several different priors. Underwater optical imaging models divide the light reaching the imaging system into three components: direct, forward-scattering and backward-scattering. Researchers improve the restoration quality by: adding priors on wavelength attenuation and blurring, adding priors on brightness, and modifying the imaging model based on the background light shift assumption [11,12].

Polarisation techniques involve acquiring polarised images of the underwater scene. They undo image degradation by disentangling background and scattered light, and estimating light intensity and transmittance. The latest developments in this area include synthetic aperture polarimetric imaging, periodic polarised image integration, and polarisation-difference methods, which are typically accompanied with improved metric constraints and noise removal [13,14]. The most popular prior-based approaches are the Dark Channel Prior (DCP) and its variants. DCP is based on the assumption that non-sky pixels in haze-free images have at least one dark channel that has low intensity. To improve its effectiveness, DCP has been enhanced with brightness adjustment, colour compensation, dark-bright dual-channel algorithms and depth-dependent ambient light modelling. This helps to enhance contrast, correct colour distortions and remove blurring [15,16]. To improve the performance of single priors, researchers have suggested other optimisation techniques, including the equalisation of attenuation coefficients for multiple colour channels and multi-prior approaches. Popular multi-prior techniques include quadtree hierarchical search, Rayleigh-distributed histogram stretching, and adaptive multi-prior integration [17,18]. In addition to DCP, many other priors tailored to underwater conditions, such as Maximum Intensity Prior (MIP), Red Channel Prior (RCP) and Underwater Light Attenuation Prior (ULAP) have been developed, providing more specific solutions for various underwater scenes [19,20].

In general, physical model-based methods have good interpretability, real-world restoration outcomes, and can be optimised for different underwater scenarios with specific strategies. But they are highly sensitive to prior knowledge. Meanwhile, complex algorithm design, difficult model parameter optimisation, and the inherent variability of underwater imaging all limit their practical application.

### 3.3. Deep learning-based methods

Deep learning-based approaches have emerged as the dominant technical framework for underwater image restoration and enhancement. These methods mainly adopt convolutional neural networks (CNNs) and generative adversarial networks (GANs). They learn non-linear mapping relationships to solve common underwater image defects, including colour distortion, low contrast and blurring [21,22]. For image restoration tasks, researchers focus on estimating key parameters of the underwater imaging model, such as transmission maps and background light.

This estimation is implemented through various network architectures, including parallel CNNs, joint residual networks and multi-scale cyclic GANs. These methods are often combined with colour correction or attenuation priors to reverse image degradation. To tackle the scarcity of paired reference images, some methods are independent of reference data, and only adopt image quality metrics to guide model training [23]. For enhancement tasks, the aim is to directly generate high-clarity, high-contrast outputs by constructing end-to-end networks, with notable contributions including underwater GANs, real-world underwater enhancement datasets, scene-prior-based CNNs, colour correction and dehazing subnetworks, multi-scale two-colour-space networks, goal-oriented perceptual adversarial fusion networks, and dual-supervised GANs [24].

Despite these advances, while early problems of low contrast and colour distortion have been gradually resolved, deep learning methods often impose high demands on hardware equipment and massive training data, which to some extent limits their application scope and operational effectiveness.

## 4. Underwater image restoration datasets

High-quality underwater image datasets play a core role in multiple research links. They support the training of data-driven networks, verify the effectiveness of image enhancement algorithms, complete model validation, and enable fair evaluation of the performance of various enhancement and restoration methods.This paper sorts out and summarizes seven representative underwater image enhancement datasets released in recent years. Most of these datasets were published between 2018 and 2025. Over time, the scale of these datasets has continued to expand, and their content diversity has also shown a steady climb trend.

SQUID and RUIE are early small-scale datasets [25]. SQUID contains 57 image pairs, with content focusing on coral reefs and shipwrecks. RUIE has more than 4,000 image pairs, mainly covering marine organisms such as scallops and sea urchins. HICRD provides a large collection of real underwater coral reef images and their restored versions. However, this dataset does not cover all types of water environments. LSU and UIDEF are both large-scale paired datasets [26,27]. LSU focuses on marine environments and rock scenes. UIDEF includes 9,200 image pairs, with resolutions up to 1080P and 640P. UID2021 uses generative methods to expand its image volume [28]. It also covers a wide range of underwater scene types. The latest dataset among them is UMDKI, released by the Harbin Institute of Technology [29]. It contains 7,245 paired images of indoor scenes rendered in an underwater style. Overall, existing datasets have made continuous progress in scale, scene diversity and image quality. But there are still unsolved challenges. For example, some datasets have incomplete coverage of water types, and some have relatively low image resolution.

## 5. Underwater image quality evaluation metrics

In terms of quantitative evaluation, the experimental results from different methods are mainly analysed using five representative metrics: Average Gradient (AG), Information Entropy (IE), Patch-based Contrast Quality Index (PCQI), Underwater Image Quality Metric (UIQM), and Underwater Colour Image Quality Evaluation Metric (UCIQE). For qualitative assessment, subjective evaluation is built around human visual perception and practical experience. Observers are organized to assign direct scores to the images. This method can effectively reflect human sensitivity to key image information, including details, contrast and color. It also captures the overall naturalness and realism of the image.

The results of this method align better with real usage experience. However, it is easily affected by factors like individual differences between observers and the observation environment. This leads to a certain degree of subjectivity and unstable results. In addition, latency is used as a core metric. It measures the time a model takes to process a single image, and directly reflects the operating efficiency of the algorithm in real scenarios. Existing methods are usually tested on CPU or GPU platforms. Test results will naturally vary across hardware with different architectures.

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## 6. Conclusion

This paper takes a close look at the physical reasons behind underwater image degradation. It also examines how image degradation shows different characteristics in different water conditions. All this analysis builds a clear theoretical foundation for designing better image repair methods. We group all current image repair technologies into three main types: physical model-based, non-physical model-based, and deep learning-based methods. We compare the pros, cons, and combined use trends of these three types of methods. We also sum up the latest research progress in mixing physical rule guidance with deep learning. In addition, we sort through the most widely used underwater image datasets and image quality evaluation standards. All this work provides a clear reference system for testing and comparing different algorithms. Even with the recent improvements in this field, putting underwater image repair methods into real use still faces four key challenges: (1) Models cannot work well in new, unseen scenes, especially when dealing with complex mixed types of image quality loss; (2) Image generation models need too much computing power, so they cannot run smoothly and quickly on underwater robots with limited hardware performance; (3) Many image processing methods focus on adjusting pixels directly. This often damages important visual features that AI needs to recognize image content; (4) Research development is held back by two main problems: not enough real-scene image datasets, and imperfect evaluation standards. These standards often care more about exaggerated, unnatural color brightness than the real physical accuracy of the image.

Future research in this field should focus on the following four key directions: (1) Build lightweight model structures (such as Vision Mamba) to make models easier to use in real scenes, and help them work better in different environments; (2) Combine deep learning with physical rules and multi-modal data such as acoustic and polarization information. We will also develop underwater 3D reconstruction technologies based on NeRF and Gaussian Splatting; (3) Create datasets that are physically accurate and grouped by water turbidity levels, and build new evaluation standards guided by Vision-Language Models (VLMs). These research improvements will help underwater vision systems be more widely used in real work. They can support more reliable applications in complex ocean engineering projects and automatic underwater robot tasks.

## References

[1] W. D. Zhang, L. L. Dong, T. Zhang, and W. H. Xu, "Enhancing underwater image via color correction and Bi-interval contrast enhancement, " Signal Process., Image Commun., vol. 90, p. 116030, 2021.
[2] S. M. Pizer, E. P. Amburn, J. D. Austin, et al., "Adaptive histogram equalization and its variations, " Comput. Vis. Graph. Image Process., vol. 39, no. 3, pp. 355-368, 1987.
[3] K. Zuiderveld, "Contrast limited adaptive histogram equalization, " in Graphics Gems IV, USA: Academic Press, 1994, pp. 474-485.
[4] P. X. Zhuang, C. Y. Li, and J. M. Wu, "Bayesian retinex underwater image enhancement, " Eng. Appl. Artif. Intell., vol. 101, p. 104171, 2021.
[5] P. X. Zhuang, J. M. Wu, F. Porikli, and C. Y. Li, "Underwater image enhancement with hyper-laplacian reflectance priors, " IEEE Trans. Image Process., vol. 31, pp. 5442-5455, 2022.
[6] C. H. Yue, H. X. Xu, F. T. Lü, et al., "Underwater image enhancement method based on illumination compensation and pyramid fusion, " J. Unmanned Undersea Syst., vol. 33, no. 1, pp. 46-55, 2025.
[7] J. Y. Yuan, Z. C. Cai, and W. Cao, "TEBCF: Real-world underwater image texture enhancement model based on blurriness and color fusion, " IEEE Trans. Geosci. Remote Sens., vol. 60, p. 4204315, 2022.
[8] J. Han, M. Shoeiby, T. Malthus, et al., "Underwater image restoration via contrastive learning and a real-world dataset, " Remote Sens., vol. 14, no. 17, p. 4297, 2022.
[9] M. Iqbal, M. M. Riaz, S. S. Ali, et al., "Underwater image enhancement using Laplace decomposition, " IEEE Geosci. Remote Sens. Lett., vol. 19, p. 1500105, 2020.

DOI: 10.54254/2755-2721/2026.AD33220


[10] D. J. Jobson, Z. Rahman, and G. A. Woodell, "Properties and performance of a center/surround retinex, " IEEE Trans. Image Process., vol. 6, no. 3, pp. 451-462, 1997.

[11] Z. Liang, X. Y. Ding, Y. F. Wang, X. H. Yan, and X. P. Fu, "GUDCP: Generalization of underwater dark channel prior for underwater image restoration, " IEEE Trans. Circuits Syst. Video Technol., vol. 32, no. 7, pp. 4879-4884, 2022.

[12] Y. Zhou, X. T. Gu, and Q. W. Li, "Underwater image restoration based on background light corrected image formation model, " J. Electron. Inf. Technol., vol. 44, no. 10, pp. 3363-3371, 2022.

[13] Y. Tian, B. Liu, X. Y. Su, L. P. Wang, and K. Li, "Underwater imaging based on LF and polarization, " IEEE Photon. J., vol. 11, no. 1, p. 6500309, 2019.

[14] J. J. Wang, M. J. Wan, G. H. Gu, W. X. Qian, K. Ren, Q. Y. Huang, and Q. Chen, "Periodic integration-based polarization differential imaging for underwater image restoration, " Opt. Lasers Eng., vol. 149, p. 106785, 2022.

[15] X. Li, Z. Yang, M. Shang, et al., "Underwater image enhancement via dark channel prior and luminance adjustment, " in Proc. OCEANS MTS/IEEE, Shanghai, China, 2016, pp. 1-5.

[16] R. Yang, Z. L. Liu, and X. Z. Zhao, "Underwater image enhancement algorithm based on color correction and dark-bright dual-channel prior, " Infrared Technol., vol. 46, no. 9, pp. 984-993, 2024.

[17] D. Berman, D. Levy, S. Avidan, and T. Treibitz, "Underwater single image color restoration using haze-lines and a new quantitative dataset, " IEEE Trans. Pattern Anal. Mach. Intell., vol. 43, no. 8, pp. 2822-2837, 2021.

[18] W. Y. Ge, Y. Lin, Z. Y. Wang, and T. Y. Yang, "Multi-prior underwater image restoration method via adaptive transmission, " Opt. Express, vol. 30, no. 14, pp. 24295-24309, 2022.

[19] A. Galdran, D. Pardo, A. Picón, et al., "Automatic red-channel underwater image restoration, " J. Vis. Commun. Image Represent., vol. 26, pp. 132-145, 2015.

[20] W. Song, Y. Wang, D. Huang, et al., "A rapid scene depth estimation model based on underwater light attenuation prior for underwater image restoration, " in Proc. Adv. Multimedia Inf. Process. (PCM), Cham, Switzerland: Springer, 2018, pp. 678-688.

[21] Y. S. Shin, Y. Cho, G. Pandey, et al., "Estimation of ambient light and transmission map with common convolutional architecture, " in Proc. OCEANS MTS/IEEE, Monterey, CA, USA, 2016.

[22] W. V. Barbosa, H. G. B. Amaral, T. L. Rocha, et al., "Visual-quality-driven learning for underwater vision enhancement, " in Proc. IEEE Int. Conf. Image Process. (ICIP), 2018, pp. 3933-3937.

[23] J. Y. Lu, N. Li, S. Y. Zhang, Z. B. Yu, H. Y. Zheng, and B. Zheng, "Multi-scale adversarial network for underwater image restoration, " Opt. Laser Technol., vol. 110, pp. 105-113, 2019.

[24] C. Y. Li, C. L. Guo, W. Q. Ren, R. M. Cong, J. H. Hou, S. Kwong, and D. C. Tao, "An underwater image enhancement benchmark dataset and beyond, " IEEE Trans. Image Process., vol. 29, pp. 4376-4389, 2020.

[25] R. Liu, X. Fan, M. Zhu, et al., "Real-world underwater enhancement: Challenges, benchmarks, and solutions under natural light, " IEEE Trans. Circuits Syst. Video Technol., vol. 30, no. 12, pp. 4861-4875, 2020.

[26] L. Peng, C. Zhu, and L. Bian, "U-shape transformer for underwater image enhancement, " IEEE Trans. Image Process., vol. 32, pp. 3066-3079, 2023.

[27] L. Chang, H. Song, M. Li, et al., "UIDEF: A real-world underwater image dataset and a color-contrast complementary image enhancement framework, " ISPRS J. Photogramm. Remote Sens., vol. 196, pp. 415-428, 2023.

[28] G. Hou, Y. Li, H. Yang, et al., "UID2021: An underwater image dataset for evaluation of no-reference quality assessment metrics, " ACM Trans. Multimedia Comput., Commun., Appl., vol. 19, no. 4, pp. 1-24, 2023.

[29] P. Lv, F. Zha, X. Wang, et al., "UMIENet: Underwater image enhancement based on multi-degradation knowledge integration, " Opt. Lasers Eng., vol. 193, p. 109069, 2025.