Journal of
Marine Science and Engineering

MDPI

Review

Breakthrough Underwater Physical Environment Limitations on Optical Information Representations: An Overview and Suggestions

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Abstract: Underwater optics have seen a notable surge of interest in recent years, emerging as a critical medium for conveying information crucial to underwater resource exploration, autonomous underwater vehicle navigation, etc. The intricate dynamics of underwater optical transmission, influenced by factors such as the absorption by the water and scattering by multiple particles, present considerable challenges. One of the most critical issues is that the optical information representation methods fail to take into account the impact of the underwater physical environment. We conducted a comprehensive review and analysis of recent advancements in underwater optical transmission laws and models. We summarized and analyzed relevant research on the effects of underwater particles and turbulence on light and analyzed the polarization effects in various environments. Then, the roles of various types of underwater optical propagation models were analyzed. Although optical models in complex environments are still mostly based on Monte Carlo methods, many underwater optical propagation mechanisms have been revealed and can promote the impacts of optical information expression. We delved into the cutting-edge research findings across three key domains: the enhancement of underwater optical image quality, the 3D reconstruction from monocular images, and the underwater wireless optical communication, examining the pivotal role played by light transmission laws and models in these areas. Drawing upon our extensive experience in underwater optics, including underwater optical sensor development and experiments, we identified and underscored future directions in this field. We advocate for the necessity of further advancements in the comprehension of underwater optical laws and physical models, emphasizing the importance of their expanded application in underwater optical information representations. Deeper exploration into these areas is not only warranted but essential for pushing the boundaries of current underwater optical technologies and unlocking new potential for their application in underwater optical sensor developments, underwater exploration, environmental monitoring, and beyond.

Keywords: underwater optical transmission; underwater optical image; 3D reconstruction; underwater optical communication; deep learning

Citation: Li, S.; Zhang, Z.; Zhang, Q.; Yao, H.; Li, X.; Mi, J.; Wang, H. Breakthrough Underwater Physical Environment Limitations on Optical Information Representations: An Overview and Suggestions. *J. Mar. Sci. Eng.* **2024**, *12*, 1055. https://doi.org/10.3390/jmse12071055

Academic Editors: Adriano Mancini, Anna Nora Tassetti and Pierluigi Penna

Received: 23 April 2024
Revised: 2 June 2024
Accepted: 17 June 2024
Published: 23 June 2024

1. Introduction

The ocean harbors a wealth of biological and mineral resources, including marine fish and seabed oil. As terrestrial resources are increasingly depleted and the demand for modern industrial development grows, the exploration and utilization of marine resources have emerged as a vital strategy for coastal countries. In this context, acquiring precise and clear environmental and target information in the variable and largely uncharted underwater realms of the ocean is crucial for the accurate surveying and rational exploitation of these resources [1,2]. Underwater optical information, characterized by its rich colors, distinct boundaries, and diverse dimensions and types of information, significantly enhances the precision of resource exploration efforts. It facilitates the discovery of deep-water biological entities and the exploration of seabed minerals, positioning itself as a critical medium for underwater data collection and one of the essential methods for accessing marine resource information [3,4].

However, light propagation in water is significantly influenced by absorption and scattering, with the underwater environment further complicated by the presence of irregular particles, turbulence, and other phenomena. These factors lead to the rapid attenuation of underwater light energy and non-uniform attenuation rates, which in practical applications manifest as instability in the information carried by light. Consequently, underwater optical information often appears blurred or distorted. The advent of substantial advancements in optical equipment has catalyzed interest in underwater optical information perception, marking its wide-ranging application, especially with the integration of deep learning technologies [5]. This integration has propelled underwater image enhancement, 3D reconstruction, and optical communication to the forefront of research and practical applications.

The Xi'an Institute of Applied Optics, 705 Research Institute of China State Shipbuilding Corporation Limited (CSSC), and Shaanxi University of Science and Technology have engaged extensively in underwater optical experiments, including seawater blue–green laser transmission, light transmission in bubble-containing water mediums, underwater optical imaging, and underwater target range gating, etc. We have generated a vast dataset, shedding light on the complex and dynamic nature of underwater environments and the significant challenges posed to light transmission and imaging therein. From an engineering perspective, we have tackled numerous challenges associated with underwater light transmission. Innovations such as optical range gating amidst underwater environmental disturbances and the automatic acquisition of imaging parameters in bubble-containing environments represent key advancements.

However, the inherent underwater physical environments limit the ability of shedding light on information expression, although deep learning methods yielded promising results across various underwater optical scenarios. The relatively poor interpretability of deep learning poses challenges for its application in architecture design, parameter setting, and hardware integration. It is significant to bridge these gaps by providing a comprehensive analysis and insights of the underwater physical principles and optical models by reviewing recent advancements. We integrate these latest theories and models in three aspects: enhancement of underwater image quality, 3D reconstruction from underwater monocular optical images, and underwater wireless optical communication. We attempt to improve the information representation ability of light and propose directions for future research, as depicted in Figure 1. We advocate for a closer integration of physical models with deep learning approaches. Such integration is pivotal for advancing the understanding of underwater optical transmission principles and fostering the broader application of technologies. Through this review, we aim to spur further research and application breakthroughs in these critical areas.

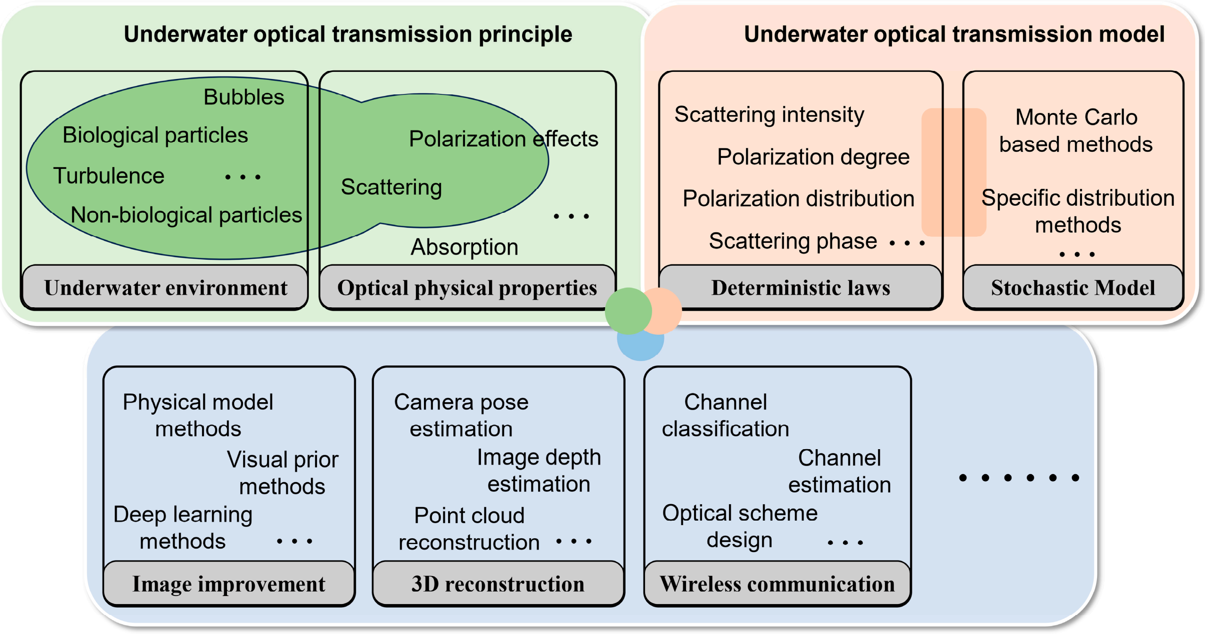


Figure 1. Research on underwater optics.

2. Underwater Influences on Light

As light propagates through water, it is subjected to absorption and scattering, influenced by water and underwater particles, such as sand, plankton, and dissolved organic matter. Figure 2 depicts the attenuation process of light as it travels underwater. The light intensity is range-dependent, and red light is absorbed stronger, succeeded by other longer wavelengths. At 20 m, only blue and green wavelengths are discernible, and at approximately 30 m, exclusively blue light prevails. It must be emphasized that prevalence of blue light exists only in clear water, and green light propagates farther than others in some contaminated water. The distance determines selective absorption and the profound impact on the spectral composition of underwater light. The propagation process is described by the Lambert–Beer theorem:

$$E_r = E_0^{-(\sigma+\gamma)d} \quad (1)$$

where E_0 is the optical intensity when depth is 0, E_r is the attenuated optical intensity, d is the depth, while σ and γ are the absorption coefficient and scattering coefficient, respectively.

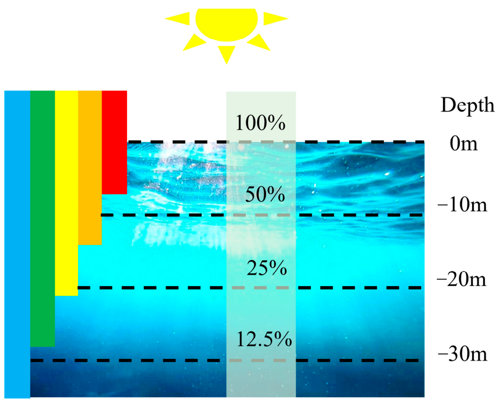


Figure 2. Optical attenuation process underwater.

Light is affected by water flow and particles. This interaction between light and water molecules or suspended particles alters the trajectory of light rays, causing them to veer from their original path. As illustrated in Figure 3, underwater optics can be categorized into three components: direct, forward-scattered, and backward-scattered. The direct component consists of light from the source that directly reaches and reflects back from the target to the receiver. The forward-scattered component comprises light that, although reflected from the target, is deflected by waterborne particles. Conversely, the backward-scattered component includes light from the source that is dispersed by particles back toward the optical device.

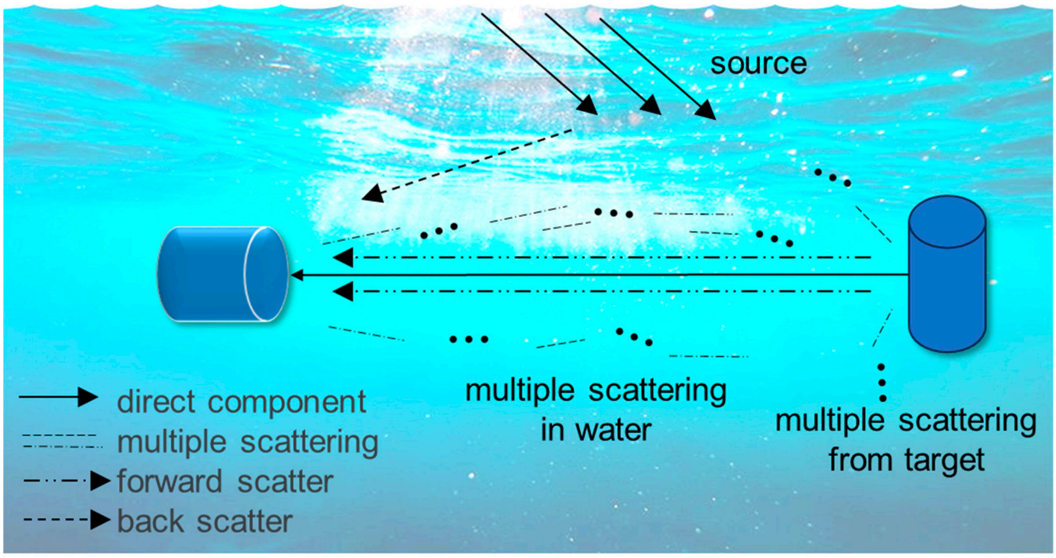


Figure 3. Underwater optical transmission.

The intricacies of how optical information is modified in complex underwater environments are yet to be fully understood. Light conveys extensive information through its color, brightness, and polarization. For instance, underwater optical imaging demands enhanced contrast and clarity, whereas underwater optical communication prioritizes stability and precision. To shed light on the recent advancements in research and their implications for improving underwater optical information expression, this review delves into the influence of complex underwater conditions on light transmission. Special focus is paid to the roles of turbulence and polarization. We seek to encourage further exploration and practical application of the findings in this field, aiming to advance our understanding and technological capabilities in underwater optical information processing.

2.1. Underwater Environment Influence on Light

The impact of the aquatic medium on light is characterized by energy intensity variations across different bands and disruptions along the light transmission path. Specifically, in marine environments, such as the ocean, which harbors abundant plankton in its surface and shallow waters, light transmission is significantly affected [6]. Research conducted in the Baltic Sea has demonstrated that the spectral absorption coefficients of suspended particulate matter, along with spectral scattering and backscattering coefficients, are intricately linked to the concentration and size distribution of particles. These relationships can be quantitatively described using statistical methods to develop parametric formulas for various inherent optical properties. This analysis allows for a detailed understanding of how particulate matter influences light absorption and scattering in aquatic environments [7]. In the Barents Sea, studies on underwater light field parameters and thermal energy absorption within the visible spectrum of the seawater column reveal that variations in chlorophyll concentration, as estimated by satellite bio-optical algorithms, have a minimal effect (30–50%) on the vertical distribution of light energy absorbed in the water column. This finding underscores the complexity of factors influencing light absorption beyond biological constituents [8]. For five distinct types of core-shell algal particles (double spheroid, quadruple spheroid, filamentous cylindrical, ring-shaped filamentous, and S-shaped filamentous) exposed to a 532 nm blue–green laser wavelength, it was observed that absorption and scattering coefficients increase with particle size. Notably, forward scattering intensity was the most pronounced, and the scattering intensity for all models diminished with an increase in the scattering angle. Larger algal models exhibited more pronounced oscillations in their scattering matrix element ratios [9]. Additionally, the sea surface microlayer (SML) exhibits unique physical, chemical, and biological characteristics distinct from the underlying subsurface water (USW). Correspondingly, the spectral absorption coefficients, volume scattering function, and particle size distribution (PSD) inherent optical properties of the SML also show marked differences [10]. This differentiation highlights the varied and complex nature of light interaction with aquatic environments, necessitating a nuanced understanding of these processes for accurate optical analysis and applications, as presented in Table 1. Research on biological particle effects involves multiple types of particulates in different areas. From our lake and sea experiments on optical transmission, biology effects occur mostly on the surface of near-shore shallow water, special biological gathering areas, and human living areas, which have obvious regional and practical effects.

Table 1. Biological particulates' effects.

No.	Type	Area
1	Plankton [6]	Surface and shallow waters
2	Concentration and size distribution of particles [7]	Baltic Sea
3	Chlorophyll concentration [8]	Barents Sea
4	Core-shell algal particles [9]	Surface and shallow waters
5	Sea surface microlayer (multi-particulates) [10]	Surface and shallow waters

In the dynamic and intricate ocean optical channel, photon scatterings increase with distance and the attenuation coefficient, resulting in an expanded received light spot. Seawater, considered a non-homogeneous medium, concentrates the energy of the downlink light spot more than in uniform seawater [11]. Within 400 nm to 500 nm, under varying turbidity levels, there is a non-linear enhancement in black and white pixel responses and scattering intensity, with a maximum color body spectral reflectance detection accuracy deviation of 5.3% [12]. At a 6500 K color temperature, the power of red (638 nm), green (520 nm), and blue (450 nm) lasers aligns with the transmission function, enabling the synthesis of white light from tri-color lasers to mitigate attenuation in transmission, particularly in seawater, where attenuation and its error margin are more significant [13]. Lidar-derived indices in southeastern Florida indicate a correlation between direct and diffuse backscatter near the coast, with lidar attenuation coefficients showing up to 57% variability in near-coast inherent optical properties [14]. Using the Henyey–Greenstein function and Monte Carlo simulations to assess photon scattering angles, the impact of underwater optical channel scattering and optical system parameters on the 3 dB optical intensity spot radius (OISR) was studied, revealing minimal influence of the laser source divergence angle in particle-dense channels [15]. Blue–green lasers generally transmit further underwater, but in highly turbid waters, red light surpasses blue–green in extinction coefficient and bandwidth performance [16]. High-speed underwater vehicle navigation can induce cavitation, affecting the angle and distribution of the bubble group intercepting the light, with received power varying based on the bubble coating absorption and thickness (0.01~1.0 μm) [17]. During seabed operations, cold seeps and hydrothermal vents revealed that both hydrothermal and cold-seep-related minerals, primarily sulfides, exhibit distinctive Raman bands between 300 and 500 Delta/cm, with consistent Raman spectra in the band position and normalized strength across mineral types [18]. The non-biological factors that affect the light propagation are diversified, as depicted in Table 2.

Furthermore, the unconventional phenomena (including high turbulence, cold seeps, and hydrothermal), such as those researched in [12], would have an unconscionable effect on light, which should be considered in optical information representations.

Table 2. Non-biological particulates' effects.

No.	Environment	Effect
1	Non-homogeneous medium [11]	Concentrates the energy of the downlink light spot more than in uniform seawater
2	Varying turbidity levels [12]	Non-linear enhancement in black and white pixel responses and scattering intensity
3	6500 K color temperature [13]	The synthesis of white light from tri-color lasers to mitigate attenuation in transmission
4	Near the coast [14]	57% variability in near-coast inherent optical properties
5	Highly turbid waters [16]	Red light surpasses blue–green in extinction coefficient and bandwidth performance
6	Cavitation [17]	Received power varying based on the bubble coating absorption and thickness
7	Cold seeps and hydrothermal vents [18]	Distinctive Raman bands between 300 and 500 Delta/cm

Both biological particles and non-biological effects substantially influence underwater light transmission. While extensive studies have examined the impact of these individual factors on light, real-world conditions frequently involve a combination of elements—such as simultaneous presence of biological entities and turbidity—along with variable medium properties, complicating the understanding of light information variation. However, if the aforementioned factors coexist, current models cannot describe the variations in different frequency bands and types of light waves. Based on our study of existing models, such a universal model would be extremely complex. We believe that quantifying or characterizing the impact of different underwater environments on light, understanding the variation patterns in underwater environments in key regions, and exploring the relationship between the environment and its impact would be the better breakthrough points and research directions in the future. Additionally, turbulence, a phenomenon more prevalent in the ocean than in the previously discussed environments, has emerged as a significant area of interest due to its influence on underwater light transmission. These complexities suggest that the principles governing light information changes under such multifaceted conditions merit further investigation.

2.2. Underwater Turbulence's Influence on Light

The investigation into the effects of underwater turbulence on light transmission has captured the interest of prominent institutions, such as Johns Hopkins University [19], University of Washington [20], University of Southern California [21], and Woods Hole Oceanographic Institution [22], since the early 2000s. This period saw the development of advanced optical tools, such as submersible holographic cameras and deep-sea laser Raman spectrometers, facilitating a range of experiments. Recent research has shifted the focus toward understanding the behavior of specialized light beams within diverse turbulent conditions.

The intricate dynamics of optical cos-Gaussian and cosh-Gaussian beams in underwater environments show that smaller displacement parameters lead to increased average transmission rates, with source size enlargement also boosting transmission rates. Kinetic energy dissipation directly correlates with transmission rates, whereas mean-squared temperature dissipation shows an inverse relationship. In temperature-induced optical turbulence, transmission rates remain consistent. However, an uptick in salinity-induced turbulence notably decreases the transmission rates for both beam types [23]. Closed-form

Rytov variance expressions are derived by the simulations of plane and spherical wave propagations, linking the scintillation index to Rytov variance across different underwater turbulence intensities [24]. High-order Bessel–Gaussian beam signals and crosstalk orbital angular momentum (OAM) states' probabilities are influenced by the propagation distance and oceanic turbulence, with receiver aperture adjustments potentially mitigating crosstalk OAM state probabilities [25]. Underwater turbulence reduces the scintillation index through effects such as piston, tilt, and astigmatism, tied to various parameters, including the ratio of temperature to salinity contributions to the refractive index spectrum [26]. Remarkably, self-focusing fields carrying OAM prove exceptionally resilient against turbulence-induced degradation, showing significantly higher peak intensities and energy transmission efficiency exceeding 70% over approximately 100 m in moderately strong oceanic turbulence, with focusing properties potentially enhanced by increasing turbulence [27]. Higher-order cosh-Gaussian beams exhibit focusing characteristics on oceanic turbulence, with beam size at the receiver plane adjusting according to the turbulence severity [28]. Laser beam array incidences in underwater turbulence reveal field correlations, affected by various factors and indicating that turbulence diminishes the field correlation of laser arrays [29]. These insights underscore the profound effect of underwater turbulence on optical transmission, underscoring an urgent need for further research to advance underwater optical communications and sensing technologies in the face of turbulence-related challenges [30]. Underwater turbulence has obvious uncertainty and non-uniformity, and its description is usually based on statistical models or averaging methods. On this basis, the influence of turbulence on light is also full of uncertainty and unpredictability. The performance of light under different types of turbulence models and parameter settings is not the same. In recent years, research has focused on the influence of different forms of turbulence on specific types of beams. Some of the closed-form solutions can be used in the characterization of optical signal changes, but they are limited to a certain beam shape or a certain environment, as shown in Table 3. Therefore, the influence of turbulence on light needs to be further strengthened to reveal its internal key changes to improve the optical information representation ability.

Table 3. Underwater turbulence effects.

No.	Turbulence Conditions	Optical Effect
1	Kinetic energy dissipation per unit mass of fluid [23]	Transmission rates remained consistent in temperature-induced optical turbulence, and the transmission rates decreased for both beam types in salinity-induced turbulence
2	Plane and spherical wave propagations [24]	Closed-form Rytov variation
3	Isotropic homogeneous oceanic turbulence [25]	High-order Bessel–Gaussian beam signal and crosstalk orbital angular momentum (OAM) states' probability variation
4	Salinity-driven underwater turbulence over the temperature-driven underwater turbulence [26]	Piston, tilt, and astigmatism, tied to various parameters, including the ratio of temperature to salinity contributions
5	Turbulence-induced degradation [27]	Higher peak intensities and energy transmission efficiency exceeding 70%
6	Ensemble average of the oceanic turbulence [28]	Higher-order cosh-Gaussian beams exhibit focusing characteristics
7	Average over the underwater turbulence statistics [29]	Laser beam array incidences reveal field correlations

Over the past five years, the study of light transmission mechanisms and behavior in turbulent environments has remained a focal point, but it appears underemphasized. Recent research efforts have concentrated on modeling and interference mitigation to address turbulence's effects on light. Despite advancements in models and applications, a gap persists in understanding the fundamental mechanisms and patterns, suggesting a need for breakthroughs in related theories. Moreover, current models do not take into account the real turbulence characteristics, such as turbulence intensity, inner and outer scales of turbulence, and anisotropy. Therefore, we believe it is imperative to study the impact of anisotropic underwater turbulence on different types of light waves, as well as the consistency of the effects of turbulence at different stages on light.

2.3. Underwater Environment's Influence on Polarization Effects of Light

Polarization, defined as the orientation of transverse wave oscillations relative to the light propagation direction, represents one of light's four primary characteristics, alongside amplitude, frequency, and phase. This attribute underscores the asymmetry in the vibration direction of light wave electric fields, offering a richer depiction of target optical properties. Polarized optical imaging, leveraging this light property, proves particularly advantageous for target detection within environments characterized by low signal-to-noise ratios, intricate backgrounds, intense scattering, and dim lighting conditions [5]. This technique's capacity to discern features under such challenging conditions underscores the potential for further exploration and application in enhancing optical imaging and communication technologies.

Light propagating along the z-axis can be represented as the composite of two light waves oscillating orthogonally along the x-axis and y-axis. If the two oscillations of a certain frequency maintain a specific relative relationship, their composite light wave will trace a three-dimensional trajectory. The oscillation components can be represented as:

$$\begin{cases} E_x(z,t) = E_x' \cos\left(\omega t - \dfrac{2\pi}{\lambda} z + \varphi_x\right) \\ E_y(z,t) = E_y' \cos\left(\omega t - \dfrac{2\pi}{\lambda} z + \varphi_y\right) \end{cases} \tag{1}$$

where ω, λ are the angular frequency and wavelength of light, respectively. E_x' and E_y' are amplitude in the x- and y-directions, respectively. φ_x and φ_y are the initial phase in the x- and y-directions, respectively. $\varphi = \varphi_x - \varphi_y$ is defined as the initial phase difference between the x- and y-directions. Both $E_x(z,t)$ and $E_y(z,t)$ propagate in the z-direction, and the z-direction-synthesized light electric field satisfies the vector equation:

$$\left(\frac{E_x}{E_x'}\right)^2 + \left(\frac{E_y}{E_y'}\right)^2 - \frac{2E_xE_y}{E_x'E_y'}\cos\varphi = \sin^2\varphi \tag{2}$$

where the form of φ determines the type of polarization. When φ is a constant, the light is elliptically polarized. When φ is an integer multiple of π, light is linearly polarized. When $\varphi = \pm\pi/2$ and $E_x' = E_y'$, light is circularly polarized. When φ is randomly changing in time, light is non-polarized. The same scene possesses multiple different polarization states, which can be described using three fundamental parameters: degree of polarization, direction of polarization, and ellipticity angle.

In structured light applications, optical anomalies, misalignments, and perturbations can alter the amplitude and phase of the spatial light pattern. However, the polarization inhomogeneity of vector-structured light remains unaffected by such disturbances, assuming they are singular in nature. This resilience is exemplified by vector vortex beams, which maintain their polarization inhomogeneity intact through highly aberrant systems, demonstrating unchanged polarization properties despite medium alterations [31]. In underwater scenarios, polarization imaging detection faces challenges as the medium modulates the polarization degree of objects, and identical materials may exhibit varied polarization characteristics. Polarization data are crucial for enhancing the detection of artificial targets, with the polarization state alterations at the underwater bubble interface significantly influenced by the observation geometry [32]. Light exhibits strong penetration at minimal incidence angles, with a gradual decay in radiation intensity. However, the polarization degree for forward and backward transmissions diverges with increasing distance [33]. Integrating a precise single-scattering model for randomly oriented spheroidal scatterers with a radiative transfer model, employing Stokes formalism, accounts for the refraction of both direct unpolarized solar radiation and 100% linearly polarized radiation at the air–water boundary, followed by single scattering. These models reveal that the non-sphericity of underwater solutes impacts light polarization characteristics [34]. The complexity of underwater polarization changes has led to the adoption of deep learning methods, which learn the correlation between an object's radiance and polarization information through dense networks [35]. Despite over fifty years of research into underwater polarization, recent efforts are still concentrated on understanding polarization traits and principles in intricate environments. Nonetheless, compared to studies on light amplitude, frequency, and phase, advancements in polarization remain limited, as shown in Table 4. Deep learning may uncover previously unrecognized patterns, yet concerns over interpretability persist. Theoretical and regulatory development lags, hampering broader application in critical domains.

Table 4. Optical type or environment effect on polarization.

No.	Optical Type or Environment	Polarization Effects
1	Singular vector vortex beam [31]	Polarization inhomogeneity is intact through highly aberrant systems
2	Underwater bubble interface [32]	Variation of objects' polarization degree
3	Vector radiative transmission in underwater bubble environment [33]	The polarization degree for forward and backward transmissions diverges with distance
4	The non-sphericity of underwater solutes [34]	Depolarization in the direct backscatter direction is highly dependent on the hydrosol size distribution for non-absorbing hydrosols; prolate spheroids cause a distinct polarization pattern

In polarized light utilization for specific tasks, challenges such as noise interference and prior limitations have spurred a series of investigative efforts. Utilizing the polar decomposition method to estimate the target Mueller matrix across the entire field of view facilitates the acquisition of polarization characteristics that exhibit global variation. This approach aids in reconstructing targets with differing optical properties by calculating illumination light with a globally varying polarization state to mitigate noise in computational imaging [36]. To address underwater signal light absorption variability with wavelength and scene depth, a novel background area selection strategy based on an automatic attenuation difference map has been proposed for de-scattering. This method estimates background light to enable color restoration through absorption compensation, leveraging intact color components and prior absorption constraints [37]. Further research employing a genetic algorithm to analyze the degree of linear polarization (DoLP) of target-reflected and backscattered light has led to enhanced target imaging with optimal contrast. By incorporating constraints to bypass ineffectual scans, this technique effectively counters natural water-scattering effects. It computes the DoLP for both target and backscattered light, proving effective for complex targets in highly scattering environments without requiring prior knowledge of the target or background [38]. Polarization imaging necessitates capturing two frames of the target in orthogonal polarization states (I-max and I-min), with imaging potentially failing in the absence of a marked difference between these states. The similarity between two images is compared and quantified using the peak correlation energy (PCE) parameter, determining the optimal image based on minimal similarity [39]. For autonomous underwater image restoration devoid of background area or prior requirements, a novel restoration method through the degradation of intermediate variables has been introduced. This approach circumvents the need for estimating intermediate variables typical in traditional underwater imaging models, accommodating underwater images with uneven lighting. It sidesteps the issue of subpar and unstable image restoration results stemming from inaccurate intermediate parameter estimations, offering a promising avenue for advanced underwater imaging applications [40]. The light polarization energy distribution, intensity, and trend can be utilized as important bases for improving the expression of optical information. However, there seems to be no unified polarization information processing method or polarization information evaluation method that can improve light expression, as shown in Table 5. Therefore, we believe that the introduction of polarization information in local tasks can effectively improve the ability of optical information expression, but in a broader task similar to deep learning, further breakthroughs in optical polarization theory are needed.

Table 5. Polarization methods for optical information expression improvement.

No.	Methods	Achievements
1	Polar decomposition method [36]	Reconstructing targets with differing optical properties with a globally varying polarization state to mitigate noise in computational imaging
2	Background area selection strategy based on an automatic attenuation difference map [37]	Enabling color restoration through absorption compensation, leveraging intact color components and absorption prior constraints
3	Analyzing the degree of the linear polarization algorithm [38]	Countering natural water-scattering effects in highly scattering environments
4	The peak correlation energy quantification [39]	Marked difference between orthogonal polarization states, I-max and I-min
5	A restoration method through the degradation of intermediate variables [40]	Estimating intermediate variables typical in traditional underwater imaging models, accommodating underwater images with uneven lighting

Polarization of light in underwater environments holds significant potential for enhancing underwater optical image recognition and 3D reconstruction, aiming to improve both the accuracy and completeness of these processes. Despite advancements over the past five years, the specific polarization patterns of light under the diverse and complex optical conditions of underwater settings are yet to be fully understood. Various methods have been proposed to further the use of polarization technology in underwater applications. However, challenges persist that hinder its widespread adoption, including issues related to the stability and precision of polarization information and understanding the patterns of disturbances affecting it. Therefore, we believe that the key theoretical focus for polarization involves the physical process of optical information evolution or degradation. In underwater environments, it is crucial to describe these physical processes and establish the connection between these processes and polarization. It is particularly important when considering the non-uniform scattering medium underwater. Additionally, the sensitivity of polarization to detailed changes might make it susceptible to environmental factors, such as turbulence. Hence, the propagation characteristics of polarization in underwater turbulence and similar environments could be a significant area for future research.

3. Underwater Optical Transmission Model

Underwater light transmission is principally influenced by absorption and scattering phenomena. Absorption involves the medium uptake of light energy, leading to the conversion of photons into thermal energy, whereas scattering causes photons to deviate from their original path due to interactions with suspended particles and water molecules, without the photons being lost. From a theoretical standpoint, the model for underwater light transmission encapsulates the principles of how light absorption and scattering vary with distance. Nonetheless, accurately depicting these principles within the multifaceted underwater environment proves to be a formidable task. The attenuation of light beams in water follows the Lambert–Beer law:

$$E_r = E_0 e^{-(a+b)r} \tag{3}$$

where E_0 is the original light intensity, E_r is the intensity of light after it travels a certain distance in water, *a* is the absorption of light in water, and *b* is the scattering of light by particles in water. The underwater light transmission process is influenced by the complex aquatic medium, making it difficult to represent *a* and *b*, and the transmission process is often modeled in a stochastic manner.

The Monte Carlo method, leveraging computational capabilities to simulate random processes for modeling intricate states, has become a pivotal tool in studying underwater light transmission. This approach facilitates the generation of channel impulse response curves for various water types and transceiver configurations, with the simulation outcomes being modeled using the Double Gamma Function (DGF) and Gaussian models [41]. Specifically, research has utilized Monte Carlo simulation alongside the Gamma function to develop a pulse response model for underwater wireless laser transmission. This model offers a closed expression for simulating underwater channel pulse responses by employing multiple Gamma functions, grounded in the analysis of seawater optical properties [42]. Further advancements include the proposal of a composite channel model that accounts for multiple bubble sizes, absorption, and scattering-induced fading. This model evaluates optical communication systems' performance in composite channels, considering varying positions, sizes, and densities of bubbles, utilizing Mie theory, geometrical optics, and the absorption-scattering model within the Monte Carlo framework. An increase in bubble quantity results in greater attenuation, reduced received power, and an elongated pulse response, with notable peaks in the volume scattering function or at critical scattering angles [43]. Additionally, the impact of different light sources, environmental conditions, and target parameters on reflected light characteristics has been analyzed. This includes the polarization degree difference between reflected and backscattered light, with a Monte Carlo numerical simulation method based on Mie scattering theory, and the polarized bidirectional reflectance distribution function employed to construct an underwater photon-scattering and reflection-tracking model. Under identical conditions, the polarization characteristic disparity between backscattered and reflected light is more pronounced with circular than with linear polarization. Moreover, the difference in reflective targets' complex refractive indices alters the polarization of reflected photons, with these indices differentially affecting the two polarization types [44]. The Monte Carlo method plays an important role in multiple underwater light models. It could model the effect of the channel impulse response and describe the influence of bubbles on light and the scattering of underwater particles, as shown in Table 6.

Table 6. Monte Carlo-based models.

No.	Monte Carlo Based Models	Achievements	Scalability
1	Combination of the Double Gamma Function and Gaussian models [41]	Facilitating the generation of channel impulse response curves for various water types and transceiver configurations	Suitable for variation of chlorophyll concentration with depth below 0.2 mg/m^3 and above 0.2 mg/m^3. Turbulence is not considered.

2	The Gamma function-based pulse response model [42]	A closed expression for simulating underwater channel pulse responses by employing multiple Gamma functions	Limitation on the turbidity of water. The particle phase function and volume scattering function are estimated.
3	A composite channel model [43]	Evaluates optical communication systems' performance in composite channels, considering varying positions, sizes, and densities of bubbles	Large bubbles are assumed spherical. Scattering direction of the photons is assumed to be uniformly distributed.
4	A Monte Carlo numerical simulation method based on Mie scattering theory and the polarized bidirectional reflectance distribution function [44]	Construct an underwater photon-scattering and reflection-tracking model	Mainly for the polarization degree of reflected and backscattered light from underwater targets. The changes during the propagation of light through the water are not considered.

Research reveals how the complex refractive indices of underwater suspended particles affect the polarization characteristics of polarized photons' forward and backward scattering, aiming to understand the influence of these particles on polarized light transmission. Utilizing Mie scattering theory, a scattering model for underwater photon transmission was established. This model incorporates Mueller matrices and the meridian plane Monte Carlo method to simulate a photon radiative transfer process in scattering media, offering insights into the interaction between polarized light and underwater particulates [45]. A semi-analytical Monte Carlo polarized radiative transfer model was developed to examine multiple scattering effects on seawater depolarization. This model revealed that the depolarization ratio of lidar return signals escalates with an increased penetration depth, the receiver field of view, single scattering albedo, and the seawater beam attenuation coefficient, highlighting the significant role of multiple scattering in depolarizing light in seawater [46]. The impact of outer-scale turbulence on Gaussian beams' optical properties and signal temporal dispersion was analyzed using the Monte Carlo ray-tracing statistical method. Findings indicated that, under weak turbulence conditions, outer-scale turbulence significantly affects beam spreading and centroid drift of collimated Gaussian beams, though it has less impact on intensity fluctuations and only a minor effect on temporal broadening, with signal temporal dispersion showing a quadratic relationship with transmission distance under turbulence [47]. A transmission model for underwater photons, combining Mie scattering theory and Monte Carlo numerical simulation, was established to investigate how particle size influences optical transmission. Increases in particle size led to higher optical coefficients, reduced normalized energy reception, decreased light intensity, and longer channel time delays for the same transmission distance. Furthermore, particle size induced depolarization in laser transmission, more profoundly affecting linearly polarized light than circularly polarized light [48]. Integrating the Sahu–Shanmugam and Fournier–Forand volume scattering functions with the Monte Carlo method, an underwater laser transmission channel model was created. This model assesses beam spreading at the receiver end, exploring the impacts of the receiver field-of-view angle and surface diameter on beam power density, alongside the distribution characteristics of beam power density at varying receiving distances [49]. The Monte Carlo method can further describe the scattering and polarization phenomena combined with other theories. The influence of turbulence or particle size on optical transmission can be accurately described, as shown in Table 7. However, Monte Carlo-based methods mostly obtain the distribution or simulation results, and there is no fixed model or closed solution. Therefore, further promotion of this method in the characterization of optical information still needs further theoretical breakthroughs.

Table 7. Underwater particle scattering models.

No.	Interpretative Models of Underwater Particle Scattering	Achievements	Scalability
1	Mie scattering theory-based scattering model [45]	Simulates the photon radiative transfer process in scattering media, offering insights into the interaction between polarized light and underwater particulates	The particle radius and quantity is constant. Not taking into account the effects of turbulence.
2	Polarized radiative transfer model [46]	Examines multiple scattering effects on seawater depolarization	Mueller matrix of seawater is an estimate. The scattering phase function is assumed to be constant.
3	The Monte Carlo ray-tracing statistical method [47]	Analyzes the impact of outer-scale turbulence on Gaussian beams' optical properties and signal temporal dispersion	The combined effect of the outer and inner scales of turbulence is not explained.
4	Transmission model combining Mie scattering theory and Monte Carlo numerical simulation [48]	Investigates how particle size influences optical transmission	A single particle size distribution is considered. Particles underwater are assumed to be single spherical.
5	Integrating the Sahu–Shanmugam and Fournier–Forand volume scattering functions with the Monte Carlo method [49]	Assesses beam spreading at the receiver end, exploring the impacts of receiver field-of-view angle and surface diameter on beam power density	Scattering parameter and attenuation parameter are constant. Requirements for water turbidity.

In certain light signal and environmental scenarios, modeling specific parts of the transmission process or evolutionary phenomena through distinct distributions is another key approach. The authors of [50] introduced a model for perfect optical vortex (POV) beams utilizing the Rytov approximation and mutual coherence function to assess the effect of wave parameters on the orbital angular momentum (OAM) detection probability spectrum. Simulations of POV-based underwater optical wireless communication (UWOC) systems, employing a blend of Gamma–Gamma and normal distributions, revealed that transmission quality primarily depends on the beam radius, with minimal influence from wavelength, temperature contrast (TC), and radius-thickness ratio. The authors of [51] explored the transmission probabilities of signal vortex modes in oceanic turbulence using Rytov theory, showing that Mathieu–Gaussian beams with narrow initial widths, long wavelengths, and minor ellipticity parameters exhibited higher transmission probabilities compared to modes with the opposite characteristics. The impact of weak turbulence on signal vortex modes becomes negligible with an appropriate semi-cone angle. The authors of [52] presented analytical formulas for the average intensity of double-half inverse Gaussian hollow beams (DHIGHB) in oceanic turbulence, demonstrating multi-ring or single-ring configurations during propagation based on the initial beam width and turbulence strength. The authors of [53] used a tensor approach to derive the cross-spectral density function of the twisted anisotropic Gaussian Schell-model (TAGSM) beams in turbulent oceans, analyzing the beam spectral density, twist strength, and width. Results indicated that oceanic turbulence does not alter the beam spot rotation direction but leads to a Gaussian profile over long distances, with beams having larger initial twist factors, showing greater resistance to turbulence. The authors of [54] developed a spatio-temporal stochastic channel model for tracking underwater single-photon states, assessing impact factors on the received photon intensity and channel impulse response across different water types and conditions, highlighting the significance of photon information analysis at the receiver. These studies underscore the complex influence of underwater conditions on light transmission, emphasizing the need for advanced modeling to enhance underwater optical communications and sensing technologies amidst environmental challenges, as shown in Table 8.

Table 8. Transmission process or evolutionary phenomena models.

No.	The Transmission Process or Evolutionary Phenomena Model	Model Achievements
1	Perfect optical vortex beams model utilizing the Rytov approximation and mutual coherence function [50]	Assess the effect of wave parameters on the orbital angular momentum (OAM) detection probability spectrum.
2	The transmission probabilities of signal vortex modes using Rytov theory [51]	Mathieu–Gaussian beams with narrow initial widths, long wavelengths, and minor ellipticity parameters exhibit higher transmission probabilities compared to modes with the opposite characteristics.
3	Analytical formulas for the average intensity of double-half inverse Gaussian hollow beams [52]	Demonstrating multi-ring or single-ring configurations during propagation based on the initial beam width and turbulence strength.
4	A tensor approach to derive the cross-spectral density function of the twisted anisotropic Gaussian Schell-model [53]	Analyzing the beam spectral density, twist strength, and width.
5	Spatiotemporal stochastic channel model for tracking underwater single-photon states [54]	Assessing impact factors on the received photon intensity and channel impulse response across different water types and conditions, highlighting the significance of photon information analysis at the receiver.

Stochastic methods have proven effective in developing models for underwater optical transmission, yet establishing deterministic laws for transmission processes is crucial for the broader adoption of underwater optics technologies. The authors of [55] utilized the generalized Huygens–Fresnel diffraction principle to derive analytical expressions for the scattering intensity of vortex beams interacting with rough surfaces in oceanic turbulence. These expressions revealed that the complex coherence of the scattered field at the receiver diminished with increases in the vortex beam topological charge, waist radius, and wavelength, as well as with heightened oceanic turbulence intensity. The authors of [56] introduced a numerical model employing the Stokes vector and Mueller matrix, incorporating atmospheric polarization distribution, refraction at the air–water interface, and single Rayleigh scattering by water molecules. The authors of [57] detailed a mathematical model for laser radiation propagation, addressing the radiative transfer equation for a narrow beam through a simplified approximation of the seawater layer scattering indicatrix, assuming predominant forward scattering in seawater. Under the premise of pronounced forward scattering, the authors of [58] extracted three independent equations for basic modes from the exact vector radiative transfer equation, calculating the temporal profile of the polarization degree for linearly and circularly polarized pulses using actual scattering matrix data. The polarization degree exhibited a self-similar dependency on a mix of the transport scattering coefficient, temporal delay, and the distance between the source and receiver. The authors of [59] outlined formulas for computing the irradiance field in a turbid medium with a narrow scattering phase function and uniform optical properties, created by an infinitely narrow light beam. Many studies have obtained deterministic laws and fixed models of light propagation of the air–water interface, turbulence, and other environments. In the latest research, the in-depth application of such methods in optical information expression is still limited, as shown in Table 9. We suggest that methods such as the Stokes vector and Mueller matrix can be used in the key steps of optical information expression to eliminate the influence of light scattering on information expression.

Table 9. Deterministic laws for transmission processes.

No.	Deterministic Laws for Transmission Processes	Achievements
1	The generalized Huygens–Fresnel diffraction principle [55]	Analytical expressions for the scattering intensity of vortex beams interacting with rough surfaces in oceanic turbulence.
2	Numerical model employing the Stokes vector and Mueller matrix [56]	Incorporating atmospheric polarization distribution, refraction at the air–water interface, and single Rayleigh scattering by water molecules.
3	A mathematical model for laser radiation propagation [57]	Addressing the radiative transfer equation for a narrow beam through a simplified approximation of the seawater layer scattering indicatrix, assuming predominant forward scattering in seawater.
4	Three independent equations for basic modes from the exact vector radiative transfer equation [58]	Calculating the polarization degree temporal profile for linearly and circularly polarized pulses using actual scattering matrix data.
5	Formulas for computing the irradiance field in a turbid medium with a narrow scattering phase function and uniform optical properties [59]	Considers the temporal spreading of a pulsed light beam in the sea while maintaining high accuracy in depicting its spatial structure.

The underwater optical transmission process undergoes changes that significantly affect imaging, ranging, and related tasks, necessitating the development of various models. The authors of [60] introduced a comprehensive underwater imaging process model by integrating the bidirectional reflectance distribution function with the Monte Carlo method. This model simulates the real channel by incorporating particles with absorption and scattering functions into the medium, applying Mie scattering theory for enhanced realism. The authors of [61] developed an underwater target polarization reconstruction model based on radiative transfer theory and Mueller matrix analysis. It enriches the classic Schechner model with target polarization characteristics, employing the covariance method for automatic target polarization information estimation. This model facilitates polarization imaging in complex underwater scenarios featuring bubbles and suspended particles, delivering reconstruction outcomes across diverse environments and target materials. The authors of [62] presented a concise derivation and expression for the refractive fundamental matrix using a refraction camera model, addressing non-linear light distortion due to medium density changes. This foundation supports a two-view reconstruction approach for underwater imaging. The authors of [63] proposed an underwater laser ranging model that utilizes optical vortices, transforming target-reflected Gaussian beams into optical vortices with spiral-phase plates for clearer separation of the target-reflected signal from scattering clutter. The authors of [64] derived an explicit expression for the background transmission of forward-scattered light in underwater optical image restoration, calculating transmittance parameters via second-order statistics of scattered light. This wavelength-dependent color restoration method evaluates the transmittance map for each RGB channel, as shown in Table 10.

Table 10. Task-specific models.

No.	Task-Specific Models	Achievements
1	Underwater imaging process model by integrating the bidirectional reflectance distribution function with the Monte Carlo method [60]	Simulates the real channel by incorporating particles with absorption and scattering functions into the medium, applying Mie scattering theory for enhanced realism.

2	An underwater target polarization reconstruction model based on radiative transfer theory and Mueller matrix analysis [61]	Facilitates polarization imaging in complex underwater scenarios featuring bubbles and suspended particles, delivering reconstruction outcomes across diverse environments and target materials.
3	Concise derivation and expression for the refractive fundamental matrix using a refraction camera model [62]	Addressing non-linear light distortion due to medium density changes.
4	An underwater laser ranging model that utilizes optical vortices [63]	Transforming target-reflected Gaussian beams into optical vortices with spiral-phase plates for clearer separation of the target-reflected signal from scattering clutter.
5	An explicit expression for the background transmission of forward-scattered light in underwater optical image restoration [64]	Evaluates the transmittance map for each RGB channel.

For the complexity of underwater environments and optical properties in aquatic media, statistical theoretical descriptions of underwater optical transmission have become pivotal. Computational methods, such as Monte Carlo simulations and random distribution characterizations, have advanced significantly. However, accurately modeling the transmission process, including specific phenomena and occurrences, remains essential. Despite substantial research and application of underwater optical transmission models in various tasks, challenges persist in deeply integrating phenomenon-specific and random descriptions, representing underwater optical physical laws in transmission models, and leveraging the expanding wealth of prior information due to advancements in sensor and computer technology. Further research is required to concisely mathematically characterize underwater optical physical laws and integrate them with transmission models, exploring the impact of extensive prior information on these models.

4. Underwater Optical Information Representations

Based on the foundational research into underwater optical physical laws and transmission models, the application of underwater optical information has seen notable advancements. These developments are analyzed from three perspectives: the enhancement of underwater optical image quality, the 3D reconstruction of monocular optical images, and advancements in underwater optical communication.

4.1. Underwater Optical Image Quality Improvement

Underwater light transmission is subject to various scattering processes, leading to non-uniform attenuation of optical information. This phenomenon impacts underwater imaging in several ways, as follows:

(1) Uneven image brightness: The introduction of artificial light sources results in the brightest image areas being near the center, with brightness diminishing as the distance from the light source increases. This gradient effect leads to captured underwater images displaying uneven brightness levels.

(2) Low image contrast and blurriness: The absorption of light in water is influenced by pigments, suspended matter, and dissolved organic materials, whereas scattering is predominantly caused by suspended particles and bubbles. These factors collectively lead to underwater images characterized by low contrast, a blurriness effect, and diminished detail clarity.

(3) Color bias in underwater images: As light travels through water, it undergoes frequency-dependent absorption, with red light being the most strongly absorbed and blue and green light the least. This differential absorption results in underwater environments predominantly reflecting blue–green hues, imparting a characteristic color bias to underwater images.

To mitigate the challenges associated with underwater optical imaging, researchers have developed a variety of methods leveraging optical characteristics. The authors of [65] introduced an underwater image enhancement technique based on relative radiometric correction principles, specifically designed for underwater active optical imaging detection. The enhancement process is divided into two stages: brightness compensation and color restoration. Brightness compensation adjusts channel-wise compensation based on underwater point light source imaging characteristics and radiation attenuation mechanisms. The color restoration stage involves adaptive compensation and color balancing of the red channel image, followed by comprehensive color restoration using the Retinex model. The authors of [66] proposed a color correction method for underwater images that significantly enhances color fidelity by addressing the pronounced color bias prevalent in underwater imaging. The authors of [67] offered a method to correct color biases by categorizing color shifts into five classes based on RGB channel averages. The method then utilizes optical attenuation characteristics to calculate the color loss rate across different underwater scenes. The authors of [68] detailed a method for recovering underwater polarized images, employing Gaussian curvature filtering for preprocessing, partitioning images based on polarization information, and then utilizing a joint image evaluation method for complex polarized characteristic target recovery. The authors of [69] introduced an underwater image restoration method that estimates background light and calculates scene depth and transmission maps to restore the image by inverting the underwater image formation model. The authors of [70] addressed light scattering and absorption at different wavelengths using the color-line model, filtering image patches exhibiting color-line characteristics for local transmittance estimation. The authors of [71] presented an active polarization imaging method for underwater objects, incorporating an illumination homogenization technique in the frequency domain to extract and standardize natural incident light. The authors of [72] proposed a method for estimating polarization parameters using spatial and frequency domain operations, combining image information pre- and post-frequency domain filtering. For image quality monitoring in ROV display modules, the authors of [73] introduced NIPQ, which considers human visual system behavior and the specific imaging characteristics of underwater images across different water types, unlike previous models.

Deep learning techniques, employing vast datasets and complex linear/non-linear structures, have become prominent for modeling the relationship between pristine and distorted images. The push for model interpretability has spurred research employing deep learning to explore underwater optical physical properties and transmission models. The authors of [74] introduced the underwater image enhancement convolutional neural network (UWCNN) model, utilizing underwater scene priors. By merging the physical underwater imaging model with the optical characteristics of underwater scenes, a comprehensive underwater image degradation dataset was synthesized, spanning various water types and degradation levels. A tailored lightweight CNN model for each scene type was developed, trained with respective data, and subsequently applied to enhance underwater videos. Inspired by the physical underwater imaging model, the authors of [75] designed a decoder network guided by medium transmission (the proportion of scene radiance reaching the camera) to boost the response to quality-degraded regions. The network, leveraging multiple color space embeddings and blending physical and learning-based methods, significantly enhances underwater image visual quality. The authors of [76] delineated the statistical relationship between underwater and restored images based on the scattering model, introducing a novel, efficient underwater image restoration (UIR) model. This model addresses the UIR challenge by segmenting it into global restoration and local compensation, developing dedicated modules for each. Considering underwater imaging characteristics, the authors of [77] proposed a two-phase CNN for underwater image enhancement based on structural decomposition. It initially splits the original image into high- and low-frequency components, followed by a dual-phase enhancement network comprising a preliminary enhancement and refinement network. The authors of

[78] presented a multi-feature underwater image enhancement method via an embedded fusion mechanism (MFEF). They found that the quality of reconstruction results was affected by the quality of the input image to some extent, and used pre-processing to obtain high-quality images, which can improve the final reconstruction effect. The authors of [79] proposed an attention-based color consistency underwater image enhancement network, which consists of three components: illumination detail network, balance stretch module, and prediction learning module.

We utilized two non-physical model-based underwater image enhancement methods, Gamma correction (GC) and histogram equalization (HE), two physical model-based methods, underwater dark channel prior (UDCP) and image blurriness and light absorption (IBLA), and a representative deep learning method, Shallow-UWnet, to quantitatively compare the effectiveness of these underwater enhancement methods. The evaluation was conducted using four widely used metrics: peak signal-to-noise ratio (PSNR), structural similarity (SSIM), underwater image quality measure (UIQM), and underwater color image quality evaluation (UCIQE). As shown in Table 11, traditional methods may achieve better results than deep learning methods on certain metrics, and more complex methods do not necessarily produce better enhancement outcomes.

Table 11. Image enhancement methods' results.

No.	Methods	SSIM	PSNR	UIQM	UCIQE
1	GC	0.764	16.229	2.82	0.37
2	HE	0.631	13.738	2.982	0.501
3	UDCP	0.574	14.519	1.857	0.514
4	IBLA	0.72	18.95	2.197	0.482
5	Shallow-UWnet	0.813	22.661	2.926	0.377

We comprehensively researched traditional methods, including white balance, Gamma correction, sharpening, etc., and obtained the fusion of images by assigning specific weights, as demonstrated in Figures 4–6. This research particularly focused on restoring underwater images with blue–green hues, whereas traditional approaches effectively mitigate color disparities and adjust for red and blue light. However, our findings indicated that these algorithms often excel only in certain conditions, lack widespread applicability, and may result in over-enhancement and subsequent image distortion.

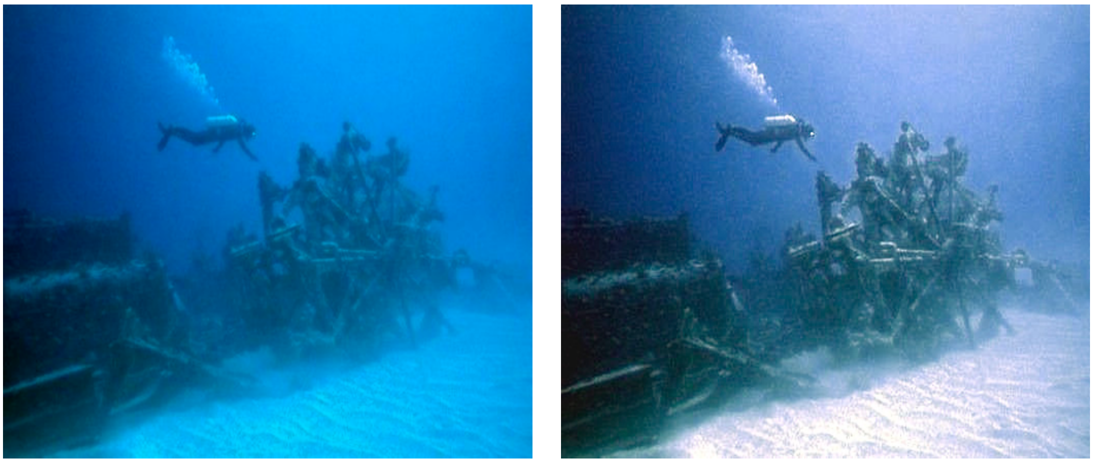
(**a**) Degraded underwater images

(**b**) Underwater image after white balance

Figure 4. Comparison of underwater images before and after white balance.

(**a**) Degraded underwater image, green tint (**b**) Fused underwater images

Figure 5. Green-tone underwater image before and after the fusion process.



(**a**) Degraded underwater image, blue tint (**b**) Fused underwater images

Figure 6. Blue-tone underwater image before and after the fusion process.

The significance of underwater optical image processing has markedly increased, as underwater infrastructure advances and the demand for economic growth intensifies. Enhancement models for optical images, grounded in the principles of underwater optical transmission and built upon transmission models, warrant further comprehensive examination. Notably, methods adept at accommodating the dynamic underwater environment represent a critical area for forthcoming research, highlighting the need for adaptable and robust solutions tailored to the complexities of underwater optics.

4.2. 3D Reconstruction Technology of Underwater Monocular Optical Images

The complexity and requirements of underwater tasks are escalating, spotlighting the importance of 3D reconstruction technology based on optical images. This area has seen notable advancements, particularly with the rapid evolution of deep learning technology, which has significantly enhanced the capability to perform 3D reconstructions in intricate underwater environments. The use of monocular underwater optical images, which depend on single-lens devices, presents more substantial challenges for 3D reconstruction compared to binocular optical images or structured light approaches. This difficulty arises not only from the inherent interference affecting underwater optical information but also from the limited data that monocular devices can gather, resulting in inadequate datasets. Moreover, monocular images intrinsically lack the detailed target or environmental structure information crucial for 3D reconstruction, challenging the effective application of underwater optical physical laws and transmission models.

Nanjing University of Information Science and Technology and China Air Separation Engineering Co., Ltd. have conducted a comprehensive review on underwater 3D reconstruction techniques, encompassing optical image methods, optical–acoustic image fusion methods, and acoustic image methods [80]. This review identified image degradation and camera calibration as pivotal scientific challenges in underwater imaging, suggesting future directions for enhancing reconstruction accuracy, integrating multimodal fusion, achieving real-time reconstruction, and improving evaluation metrics. The authors of [81] explored the 3D reconstruction of underwater ship hull surfaces using a monocular camera. The method models moderately curved hull surfaces as sequential flat panels, aligns local images within a 2D framework, and adjusts for perspective projection information, employing a simultaneous localization and mapping framework for precise camera trajectory estimation and 3D reconstruction outcomes. The authors of [82] introduced a technique for full-field 3D contour and deformation measurement underwater using single-camera stereo digital image correlation (DIC) technology. This method leverages single-side bidirectional telecentric lens imaging and dual-prism-assisted pseudo-stereo vision to create virtual images, enabling accurate 3D contour and deformation field measurements through DIC and linear equations. The authors of [83] tackled depth estimation and color correction for monocular underwater images from a multi-task perspective. An unsupervised adaptation network was proposed for joint learning, allowing for end-to-end adversarial learning-based training to estimate scene depth and correct color simultaneously. The authors of [84] proposed an underwater generative adversarial network (UW-GAN) for estimating depth from single underwater images, featuring a coarse-level generation network (UWC-Net) and a fine-level network (UWF-Net) for detailed depth map estimation. The authors of [85] presented a method for simultaneous reconstruction of surface normal and depth for dynamic underwater objects, utilizing near-infrared light absorption and surface scattering/reflection characteristics, alongside a practical calibration technique for imaging parameter determination. The authors of [86] introduced stereoscopic CNN with a multi-scale CNN transfer learning technique to mitigate the effects of bubbles or water motion on underwater objects. The authors of [87] proposed a method combining multidimensional integral imaging with time coding and deep learning for optical signal detection in turbid water bodies and obstructed environments.

Deep learning methods have marked some achievements in the domain of 3D reconstruction from monocular underwater optical images, addressing complex tasks with significant outcomes. However, these methods encounter substantial hurdles, including inaccuracies and indistinct edges in depth map estimation and point cloud reconstruction. The application of deep learning methods in this field is still limited. We verified the monocular underwater optical image 3D reconstruction results through three selected deep learning models, DenseNet [88] (3D reconstruction one), fully convolutional residual network [89] (3D reconstruction two), and AlexNet [90] (3D reconstruction three), as depicted in Figure 7. A common challenge is the limited capability to accurately capture features ranging from local contour details to overarching image characteristics. Depth prediction, particularly for distant scenes, often yields suboptimal results, with a notable inability to derive corresponding depth values at edges. As depicted in Figure 8, depth estimation one utilizes the UW-GAN, and depth estimation two utilizes a Cascaded Epipolar-based Transformer [91].

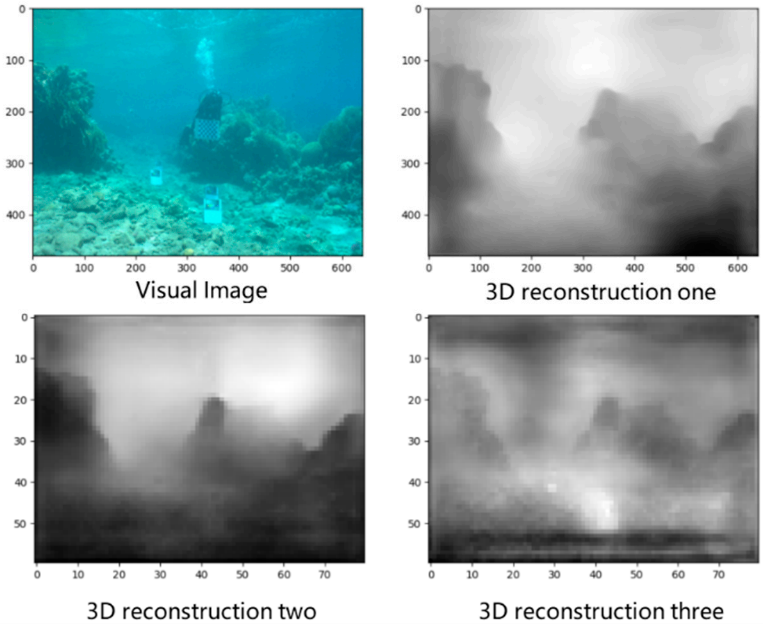


Figure 7. 3D reconstruction results.

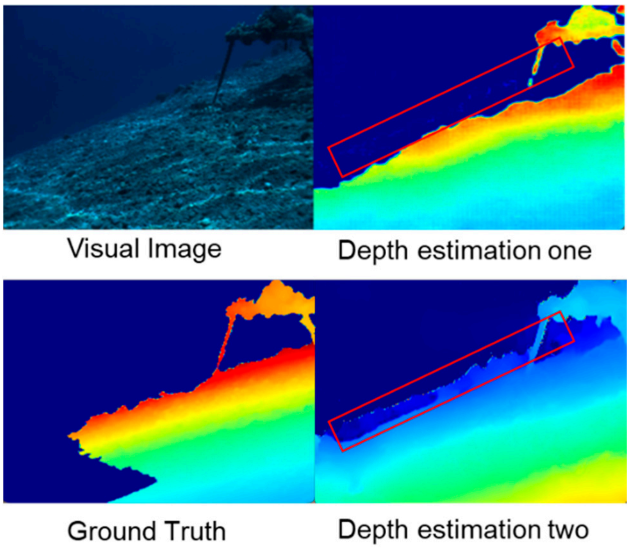


Figure 8. Depth estimation results.

The application of deep learning in enhancing the fidelity of 3D reconstruction from monocular underwater optical images necessitates substantial advancement. Currently, there is a pronounced disparity between depth prediction results, point cloud reconstruction, and the real-world underwater environment, especially concerning edge delineation, varying distances, and the reconstruction of small-scale entities. Future research could benefit from adopting a multidimensional approach, integrating data from various sources to develop a deep learning model adept at discerning the intricate patterns of underwater environments. Another promising research avenue involves combining the physical principles governing monocular underwater optics with deep learning to enhance the interpretability and applicability of 3D reconstruction technologies in underwater exploration.

4.3. Underwater Wireless Optical Communication Research

Underwater wireless optical communication technology was developed to overcome the deficiencies of acoustic communication underwater, such as long propagation delays, significant signal attenuation, severe multipath effects, and limited communication bandwidths. It features minimal environmental impact on the bandwidth, high available carrier frequencies, and low transmission delays. Underwater optical communication typically uses blue–green light beams within the 450–570 nm range, which have good directionality, high transmission rates, and strong real-time performance when passing through seawater.

Recent advancements in underwater wireless optical communication (UWOC) technology have leveraged deep learning techniques to address complex channel conditions and enhance communication performance. These studies demonstrate the potential of integrating deep learning with optical communication systems to navigate the challenges of underwater environments. The authors of [92] introduced a deep-learning-based scheme combining channel estimation (CE) and signal detection (SD) with a novel deep neural network (DNN). This approach utilizes offline training to extract channel characteristics and a DNN channel classifier for online water body identification and classification. It optimizes estimation composite weights to enhance CE/SD performance under dynamic UWOC channels. The authors of [93] employed a double Gamma function to approximate the impulse response of underwater optical links, facilitating simultaneous optimization of the encoder and decoder by learning channel characteristics. The authors of [94] highlighted that the precision of non-sequential ray tracing is contingent upon the optical properties of water and the accuracy of the scattering phase function (SPF) modeling in simulations. The authors of [95] proposed a system employing a hybrid decode–amplify–forward strategy across UWOC channels. It accounts for absorption, scattering, and misalignment effects using the beam spread function (BSF) and considers oceanic turbulence to accurately model channel characteristics. The authors of [96] discussed using a time-reversal waveform design in UWOC systems to mitigate inter-symbol interference, characterizing UWOC channels by exponential bias with random scattering effects. The authors of [97] introduced an adaptive optical (AO) technique using random amplitude masks for turbulence effect reduction in UWOC systems employing orbital angular momentum (OAM). It combines phase retrieval algorithms with a mixed exponential generalized Gamma distribution to analyze performance indicators for single and multiple inputs. The authors of [98] utilized diffractive deep neural networks (DDNN) to compensate for distortions caused by oceanic turbulence. The DDNN was trained to map the intensity distribution of vortex beam distortions to their corresponding phase screens.

Considering the advancements of wireless optical communication technology for underwater applications, particularly within the fluctuating marine environments, and considering the potential of deep neural networks, there is a pressing need for further investigation into the environmental adaptability of underwater optical communication systems. Additionally, enhancing the interpretability of deep learning algorithms related to these systems represents a critical direction for future research, aiming to optimize the performance and reliability in diverse underwater conditions.

5. Conclusions

Underwater optics has witnessed remarkable advancements in understanding transmission laws, developing predictive models, and leveraging these insights across a spectrum of underwater applications. This progress spans from exploring the fundamental physical properties influencing light propagation in aquatic settings to the creation of complex models and algorithms aimed at improving underwater imaging, 3D reconstruction, and optical communication. The propagation of light underwater is dictated by intricate interactions with water constituents, such as dissolved substances, particulates, and biological matter. A thorough grasp of these physical laws is pivotal for accurately modeling light behavior in aquatic environments, laying the groundwork for corrective strategies in imaging and communication systems. Researchers have crafted various models to emulate underwater light propagation, tackling the medium intrinsic optical challenges. These models are indispensable for the conceptualization and refinement of underwater optical systems, including both imaging apparatuses and communication pathways.

Underwater imagery often exhibits diminished visibility, color distortion, and blurriness. To mitigate these impediments, advanced image processing methods have been formulated, drawing upon both physical models and deep learning algorithms. The unpredictable nature of underwater settings presents formidable obstacles for optical image 3D reconstruction. Here, deep learning models emerge as powerful tools for deducing depth information from singular images, a task historically hampered by the lack of distinct visual markers and water's distorting influence on light. Optical communication emerges as a high-bandwidth alternative to the traditional acoustic methods used underwater, offering prospects for expedited data transfer with reduced latency. Strategies for enhancing signal integrity encompass modulation techniques involving light intensity, phase, and polarization, alongside adaptive approaches to navigate the diverse optical properties across water types.

The ongoing investigation into underwater optical phenomena, combined with breakthroughs in computational modeling and machine learning, promises to significantly augment the capabilities of underwater imaging, 3D reconstruction, and communication technologies. As the scientific community deepens its comprehension of light's complex behaviors in aquatic environments, the development of increasingly precise models and efficacious algorithms will undoubtedly pave new pathways for the exploration and exploitation of underwater realms.

Author Contributions: Conceptualization, S.L., Z.Z. and Q.Z.; formal analysis, H.Y. and H.W.; funding acquisition, S.L.; investigation, S.L., Z.Z., Q.Z., X.L. and J.M.; resources, S.L. and H.Y.; software, S.L., Z.Z. and Y.H.; validation, J.M. and H.W.; writing—original draft, S.L. and H.Y.; writing—review and editing, S.L., Z.Z. and H.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data and results supporting the overview can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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