Generating Realistic Underwater Images using a Revised Image Formation Model

Vasiliki Ismiroglou and **Malte Pedersen** and **Stefan H. Bengtson** and **Andreas Aakerberg** and **Thomas B. Moeslund**
The Visual Analysis and Perception Lab, Aalborg University
The Pioneer Centre for AI {vasilikii,mape,shbe,anaa,tbm}@create.aau.dk

Abstract

In this work, we propose an improved synthetic data generation pipeline based on the underwater image formation model with inclusion of the commonly omitted forward scattering term, while also considering a nonuniform medium. Our results demonstrate qualitative improvements over the reference model, particularly under increasing turbidity, with a selection rate of 82.5% by survey participants. Data, code, and more information can be accessed on the project page: vap.aau.dk/sea-ing-through-scattered-rays.
Keywords: forward scattering, light attenuation, synthetic data, turbidity, underwater

1 Introduction

This short paper is heavily based on our paper titled *Sea-ing Through Scattered Rays: Revisiting the Image Formation Model for Realistic Underwater Image Generation* accepted for presentation at the ICCV 2025 Joint Workshop on Marine Vision. As the workshop proceedings have not yet been published, the current text summarizes and reuses core parts of that work.

Underwater computer vision has gained significant momentum in recent years, driven largely by the growing urgency of environmental monitoring. As marine ecosystems face unprecedented threats from climate change, pollution, and overfishing, there is a need for tools that can support long-term ecological assessment and conservation efforts. However, the physical underwater environment makes collecting and analyzing data particularly hard. A major hindrance is the low visibility that comes as a result of the properties of water. Light is attenuated differently in water compared to the atmosphere, with longer wavelengths absorbed at very short depths, leading to discolorations of the footage (Mobley [1994]). Natural light does not penetrate the medium after a certain depth, making artificial lighting necessary. That in turn amplifies backscattering and introduces new degradations, such as uneven illumination (Sooknanan et al. [2012], Wang et al. [2025]).

Synthetic data generation has been widely proposed as a solution to data scarcity (Li et al. [2017], Wang et al. [2019]), particularly in the domain of image enhancement and restoration, where access to reference images is crucial. One common approach uses the underwater image formation model (IFM) to

AI in Science Conference 2025
EU2025DK

simulate various underwater effects on clean images (Hou et al. [2020], Desai et al. [2021, 2024], Wang et al. [2019], Ueda et al. [2019]). However, it often produces visually unrealistic results, especially for turbid conditions. We believe that this approach has been misrepresented in the literature, with oversimplified assumptions and formulations. Therefore, we propose improvements with a focus on better modeling and synthesizing of turbid environments.

2 Methods

Only a portion of the light that gets reflected from an underwater scene towards a camera reaches the lens uninterrupted. The rest may be scattered or absorbed due to particles of varying sizes. This process can be approximated by the underwater image formation model of Jaffe [1990] and McGlamery [1980]. In a simplified form, it is defined as:

$$\mathbf{I}(\mathbf{x}) = \mathbf{D}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) + \mathbf{B}(\mathbf{x}) \tag{1}$$

where $\mathbf{I}(\mathbf{x})$ is the degraded image, $\mathbf{D}(\mathbf{x})$ is the direct transmission, $\mathbf{F}(\mathbf{x})$ is the light scattered forward at small angles, and $\mathbf{B}(\mathbf{x})$ is the light backscattered by particles without reaching the scene.

The direct transmission, $\mathbf{D}(\mathbf{x})$, is produced through attenuation of the latent true scene radiance, $\mathbf{J}(\mathbf{x})$, which represents the image that would be captured in the absence of degradations:

$$\mathbf{D}(\mathbf{x}) = \mathbf{J}(\mathbf{x}) \cdot e^{-\beta(\lambda)\cdot \mathbf{z}(\mathbf{x})} \tag{2}$$

Here, $\mathbf{z}(\mathbf{x})$ denotes the distance from the camera to the scene, while $\beta(\lambda)$ is the medium's attenuation coefficient, defined as the sum of the absorption $a(\lambda)$ and the scattering $b(\lambda)$ coefficients, all dependent on the wavelength of light λ.

Backscattering is modeled similarly:

$$\mathbf{B}(\mathbf{x}) = B^{\infty} \cdot [1 - e^{-\beta(\lambda)\cdot \mathbf{z}(\mathbf{x}))}] \tag{3}$$

and represents the characteristic hazy veil commonly observed in underwater imagery. The value of the veil at an infinite distance is denoted by B^{∞}.

In McGlamery [1980] and Jaffe [1990] ***the forward scattering*** component is modeled to have the following form:

$$\mathbf{F}(\mathbf{x}) = \left[\left(e^{-G(\lambda)\cdot \mathbf{z}(\mathbf{x})} - e^{\beta(\lambda)\cdot \mathbf{z}(\mathbf{x})}\right) \cdot \mathbf{J}(\mathbf{x})\right] * \mathbf{H}(\mathbf{z}(\mathbf{x})) \tag{4}$$

where $G(\lambda) \leq \beta(\lambda)$ and $\mathbf{H}$ are empirical, and $*$ signifies convolution. This is a weighted and blurred version of $\mathbf{J}(\mathbf{x})$.

By assuming that forward scattering only introduces blur, Schechner and Karpel [2004] simplified the direct and forward components to be a signal of the form:

$$\mathbf{D}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) = \mathbf{D}(\mathbf{x})_{blurred} \tag{5}$$

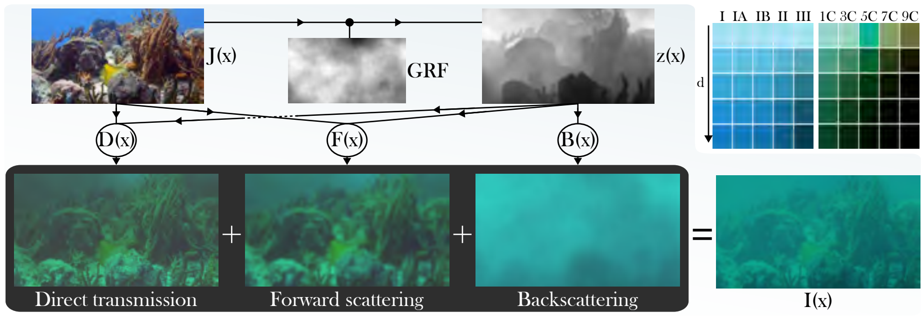

Figure 1: The proposed synthetic data pipeline. Images have been enhanced for visualization purposes. The white-patch behavior for different water types is shown on the top right (Solonenko and Mobley [2015]).

and showed that reduced contrast due to backscatter seemingly overpowers any blurring effects. Their analysis has led to the forward scattering term being overlooked in recent years.

However, when the forward scattering component is considered, the effective attenuation coefficient of $\mathbf{D}(\mathbf{x}) + \mathbf{F}(\mathbf{x})$ is G instead of β. In low turbidity environments, the coefficients are small, $G \approx \beta$, and the effect of $\mathbf{F}(\mathbf{x})$ becomes negligible. Nonetheless, as β grows and $G < \beta$, the impact of the term increases. Since the majority of light scattering happens at angles less than 90° (Tuchow et al. [2016]), potentially within the field of view of a camera, $\mathbf{F}(\mathbf{x})$ is expected to contain a sizable percentage of the captured information in scattering-heavy environments.

In this work, we reintroduce the forward scattering term into a synthetic data pipeline based on the underwater IFM. We do that by parameterizing the effective attenuation coefficient $G(\lambda)$ in eq. (4) as:

$$G(\lambda) = a(\lambda) + g \cdot b(\lambda) \tag{6}$$

Here, $g \leq 1$ represents the portion of light that scatters away from the line of sight and is an empirical value. This parametrization is consistent with recent studies in water optical properties (Tuchow et al. [2016], Doxaran et al. [2016]). We additionally address the common simplification of medium homogeneity, which can result in overly uniform turbidity effects during data synthesization. We propose a novel, general-purpose image degradation technique, using Gaussian random fields (GRFs). 2-dimensional GRFs were scaled to small values around 1, and multiplied by the attenuation coefficient of each pixel to introduce random variations in the medium.

In our proposed synthetic data pipeline, we applied the underwater IFM on clear images of underwater environments, extracting $\mathbf{z}(\mathbf{x})$ with DepthAnythingV2 by Yang et al. [2024]. Data were synthesized by varying the effective scattering coefficient g, the blur strength $\mathbf{H}$, and introducing the GRF noise.

A portion of the clear underwater images were collected in a controlled environment, where turbidity was induced using milk and clay. This provided a ground truth for comparison. Data were also synthesized with images from the EUVP dataset (Islam et al. [2020]), with attenuation coefficients taken from Solonenko and Mobley [2015]. The process is shown in fig. 1.

3 Findings

Comparisons of synthesized data with data collected in the controlled environment show that image blur is noticeable, even at short distances in turbid conditions. Including the forward scattering term results in a higher apparent similarity, especially when considering the sharpness of the underlying scene. These effects can be seen in the right part of fig. 2.

The application of GRFs to the depth maps results in more gradual and realistic haze effects while mitigating common artifacts from learning-based depth estimators, such as overly smooth or artificially rounded edges.

In order to evaluate the proposed pipeline on images without references, we collected the mean opinion ranking (MOR) through a survey. Images were randomly selected from the EUVP dataset (Islam et al. [2020]), and had their conditions synthetically altered with both the standard model and ours. 20 survey participants were then asked to choose the most realistic image between the two.

Results indicate an increase in perceived realism, with our proposed pipeline being preferred over the reference in 73.9% of the responses across all water types and 82.5% for coastal ones.

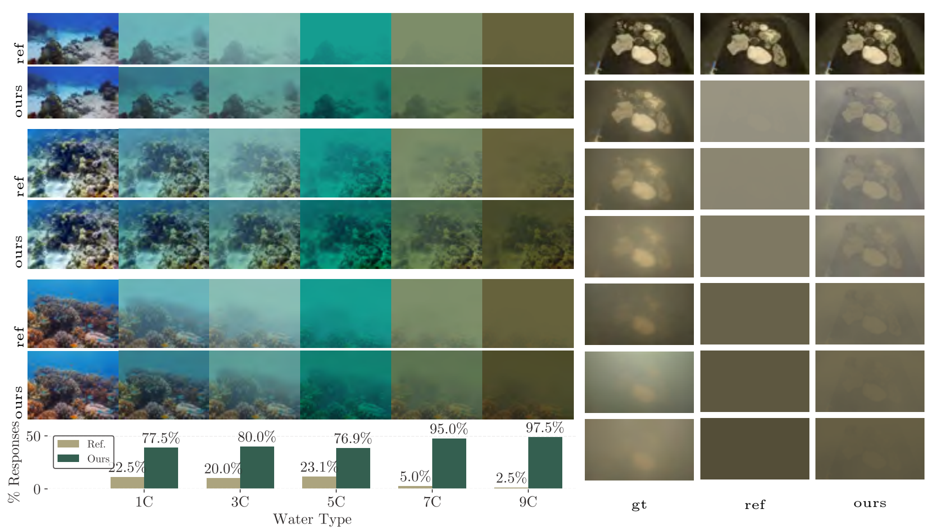

Figure 2: On the left, a comparison of our method against the reference on images from EUVP, for coastal water types. Survey results on the bottom. On the right, the same comparison for the data collected in a controlled environment.

AI in Science
Conference 2025
EU2025DK

References

C. Desai, R. A. Tabib, S. S. Reddy, U. Patil, and U. Mudenagudi. RUIG: Realistic Underwater Image Generation Towards Restoration. In *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 2181–2189, Nashville, TN, USA, June 2021. IEEE. ISBN 978-1-6654-4899-4. doi: 10.1109/CVPRW53098.2021.00247. URL `https://ieeexplore.ieee.org/document/9523078/`.

C. Desai, S. Benur, U. Patil, and U. Mudenagudi. RSUIGM: Realistic Synthetic Underwater Image Generation with Image Formation Model. *ACM Trans. Multimedia Comput. Commun. Appl.*, 21(1):10:1–10:22, Dec. 2024. ISSN 1551-6857. doi: 10.1145/3656473. URL `https://doi.org/10.1145/3656473`.

D. Doxaran, E. Leymarie, B. Nechad, A. Dogliotti, K. Ruddick, P. Gernez, and E. Knaeps. Improved correction methods for field measurements of particulate light backscattering in turbid waters. *Optics Express*, 24(4):3615–3637, Feb. 2016. ISSN 1094-4087. doi: 10.1364/OE.24.003615. URL `https://opg.optica.org/oe/abstract.cfm?uri=oe-24-4-3615`. Publisher: Optica Publishing Group.

G. Hou, X. Zhao, Z. Pan, H. Yang, L. Tan, and J. Li. Benchmarking Underwater Image Enhancement and Restoration, and Beyond. *IEEE Access*, 8:122078–122091, 2020. ISSN 2169-3536. doi: 10.1109/ACCESS.2020.3006359. URL `https://ieeexplore.ieee.org/document/9130676`. Conference Name: IEEE Access.

M. J. Islam, Y. Xia, and J. Sattar. Fast Underwater Image Enhancement for Improved Visual Perception, Feb. 2020. URL `http://arxiv.org/abs/1903.09766`. arXiv:1903.09766 [cs].

J. Jaffe. Computer modeling and the design of optimal underwater imaging systems. *IEEE Journal of Oceanic Engineering*, 15(2):101–111, Apr. 1990. ISSN 1558-1691. doi: 10.1109/48.50695. URL `https://ieeexplore-ieee-org.zorac.aub.aau.dk/document/50695`.

J. Li, K. A. Skinner, R. M. Eustice, and M. Johnson-Roberson. WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images. *IEEE Robotics and Automation Letters*, pages 1–1, 2017. ISSN 2377-3766, 2377-3774. doi: 10.1109/LRA.2017.2730363. URL `http://ieeexplore.ieee.org/document/7995024/`.

B. L. McGlamery. A Computer Model For Underwater Camera Systems. In *Ocean Optics VI*, volume 0208, pages 221–231. SPIE, Mar. 1980. doi: 10.1117/12.958279. URL `https://www.spiedigitallibrary.org/conference-proceedings-of-spie/0208/0000/A-Computer-Model-For-Underwater-Camera-Systems/10.1117/12.958279.full`.

C. Mobley. *Light and Water: Radiative Transfer in Natural Waters*. Jan. 1994. Journal Abbreviation: Academic Press Publication Title: Academic Press.

Y. Schechner and N. Karpel. Clear underwater vision. In *Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004. CVPR 2004.*, volume 1, pages 536–543, Washington, DC, USA, 2004. IEEE. ISBN 978-0-7695-2158-9. doi: 10.1109/CVPR.2004.1315078. URL http://ieeexplore.ieee.org/document/1315078/.

M. G. Solonenko and C. D. Mobley. Inherent optical properties of Jerlov water types. *Applied Optics*, 54(17):5392–5401, June 2015. ISSN 2155-3165. doi: 10.1364/AO.54.005392. URL https://opg.optica.org/ao/abstract.cfm?uri=ao-54-17-5392. Publisher: Optica Publishing Group.

K. Sooknanan, A. Kokaram, D. Corrigan, G. Baugh, J. Wilson, and N. Harte. Improving underwater visibility using vignetting correction. page 83050M, Burlingame, California, USA, Feb. 2012. doi: 10.1117/12.909134. URL http://proceedings.spiedigitallibrary.org/proceeding.aspx?doi=10.1117/12.909134.

N. Tuchow, J. Broughton, and R. Kudela. Sensitivity analysis of volume scattering phase functions. *Optics Express*, 24(16):18559–18570, Aug. 2016. ISSN 1094-4087. doi: 10.1364/OE.24.018559. URL https://opg.optica.org/oe/abstract.cfm?uri=oe-24-16-18559. Publisher: Optica Publishing Group.

T. Ueda, K. Yamada, and Y. Tanaka. Underwater Image Synthesis from RGB-D Images and its Application to Deep Underwater Image Restoration. In *2019 IEEE International Conference on Image Processing (ICIP)*, pages 2115–2119, Sept. 2019. doi: 10.1109/ICIP.2019.8803195. URL https://ieeexplore.ieee.org/document/8803195/. ISSN: 2381-8549.

N. Wang, Y. Zhou, F. Han, H. Zhu, and Y. Zheng. UWGAN: Underwater GAN for Real-world Underwater Color Restoration and Dehazing. *ArXiv*, Sept. 2019. URL https://www.semanticscholar.org/paper/ad8fbe003c65c15429ffa1a81fbd311f9bbae777.

Y. Wang, Y. Ma, Y. Li, J. Zhang, Z. Mi, and X. Fu. Underwater Vignetting Image Correction Based on Binary Polynomial Regularization and Latent Low-Rank Representation. *IEEE Transactions on Circuits and Systems for Video Technology*, 35(4):3410–3425, Apr. 2025. ISSN 1558-2205. doi: 10.1109/TCSVT.2024.3504000. URL https://ieeexplore.ieee.org/document/10759751.

L. Yang, B. Kang, Z. Huang, Z. Zhao, X. Xu, J. Feng, and H. Zhao. Depth Anything V2, Oct. 2024. URL http://arxiv.org/abs/2406.09414. arXiv:2406.09414 [cs].