DepthCue: Restoration of Underwater Images Using Monocular Depth as a Clue

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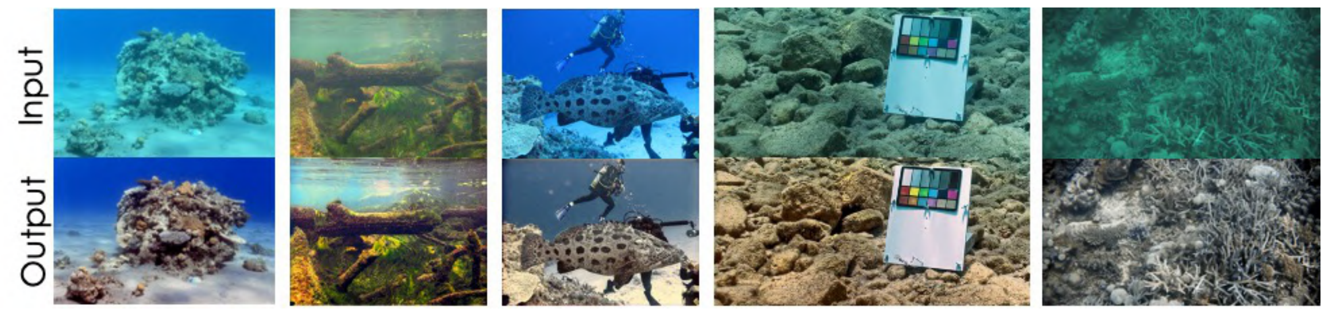

Figure 1: Results of restoration with the proposed DepthCue model.

Abstract

In this paper, we perform restoration of underwater images by considering principles of the image formation model in deep neural networks. Typically, underwater images suffer from blur, color loss and other degradations due to the scattering and absorption of light in water as a medium. Quality of restoration is sensitive to depth as scattering and absorption of light increases with depth and introduces a considerable amount of degradation. However, from literature we infer, recent restoration frameworks do not consider the influence of depth on restoration of underwater images. Towards this, we propose to consider depth as a clue for restoration considering relative distance of objects in the scene. We introduce depth with different scales as a clue for learning restoration and term the proposed architecture as DepthCue. We foresee to facilitate the restoration by eliminating the effect of degradations like lost color, blur and noise. We demonstrate our results on benchmark datasets and compare with the state-of-the-art restoration techniques using various quality metrics.

1. Introduction

Typically, underwater vision applications suffers from blur, color distortions, and low contrast due to scattering and absorption of light in water as a medium. Images captured in mist, fog, smog, smoke, and water are likely to undergo degradations as light reaching the camera passing through these mediums is either scattered or absorbed. The process of restoration in underwater scenario is more sensitive to absorption and scattering parameters such as depth, reflectance, absorption spectrum, and spectral responses of the objects in scene. From the literature, we infer quality of restoration in underwater scenario is limited by unavailability of depth information. In this paper, we propose to estimate relative depth in underwater scene, and use the same as a clue for restoration of underwater images. Few results of restoration with DepthCue is shown in Figure 1. Applications like coral reef monitoring, tracking of aquatic flora and fauna, recognition of species, and preservation of underwater archeology demands restoration and enhancement of underwater images.

Sensor artifacts initiate non linear distortions in the captured images limiting the performance of vision tasks like tracking detection, and segmentation. Image enhancement and restoration frameworks can alleviate the quality of the underwater images. Enhancement of underwater images [20] [31] has taken considerable leap as it is subjective process and does not include complex image formation model. Several techniques [11] have been proposed to improve the quality of underwater images, right from simple light enhancement to deep learning methods.

State of the art restoration techniques address underwater images restoration from several perspectives based on

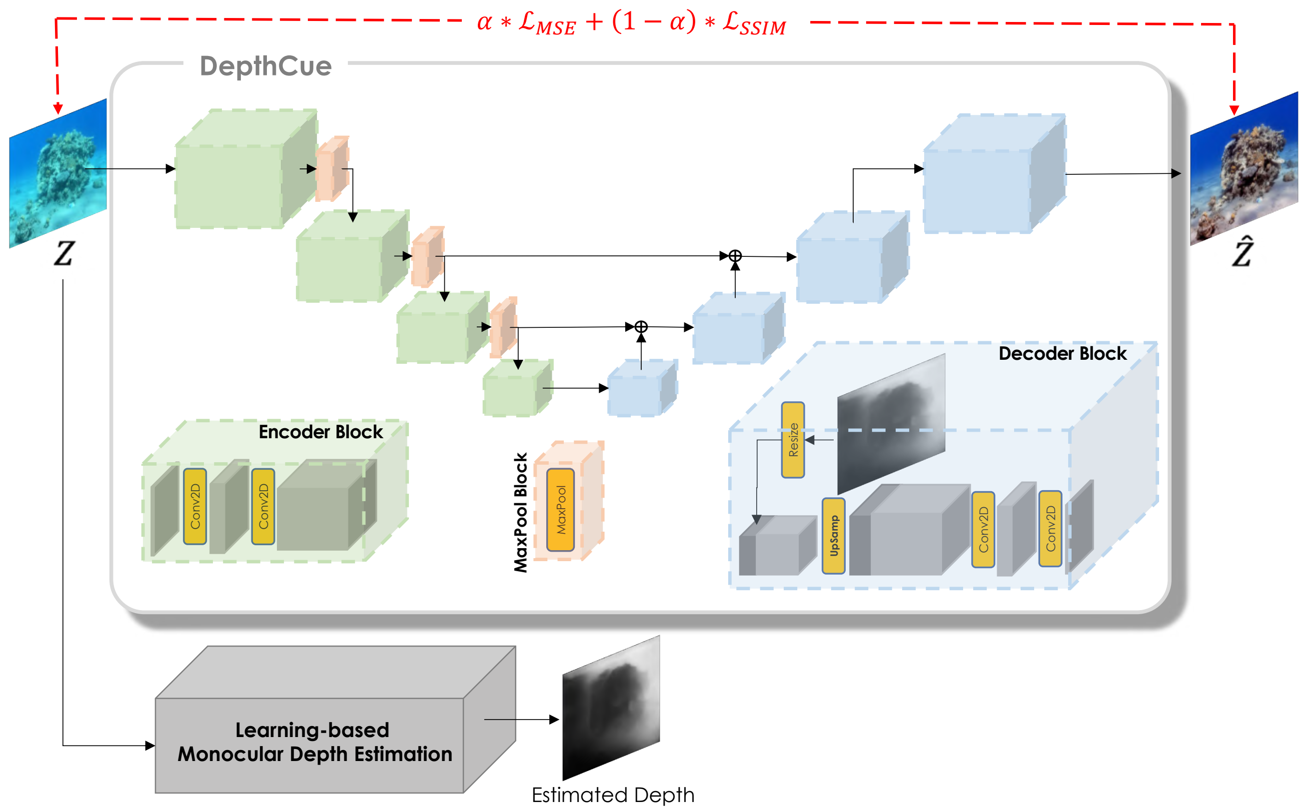

Figure 2: Proposed framework (DepthCue) for restoration of underwater images.

In-situ measurements [1], stereo vision techniques [1], traditional [25], and revised image formation models [2] [10] [8]. In-situ measurements are expensive and infeasible. In stereo vision, finding pixel correspondence is challenging in underwater scenario. The authors [25] consider traditional image formation model for restoration of underwater images. Image formation process is sensitive to both inherent and apparent optical properties. However traditional image formation model considers limited no of inherent and apparent optical properties towards restoration of underwater images.

Typically, attenuation of light in underwater scenario is influenced by direct scattering, forward scattering, backscattering and is sensitive to the presence of submerged particles. The total light reaching the camera from the object is represented as sum of direct scattering, back scattering, and forward scattering [29] as shown in Equation 1:

$$I_\lambda = D_\lambda + B_\lambda + F_\lambda \tag{1}$$

where I_λ is the total irradiance received by the camera, D_λ is the direct light, B_λ is backscattered light, F_λ is forward scattering component respectively. The subscript λ represents the wavelength of color channels R, G, and B for an RGB image. However, authors in [34] show quantitatively $F_\lambda \ll D_\lambda$, and it does not contribute significantly to the degradation of an underwater image. Therefore, Equation 1 is simplified as:

$$I_\lambda = D_\lambda + B_\lambda \tag{2}$$

Both B_λ and D_λ given in Equation 2 account for absorption and scattering independently. The direct and back scattering components are represented using wide band attenuation coefficients β_c^B and β_c^D respectively.

Traditional model as shown in Equation 3 and Equation 4 assume wide band attenuation coefficients is uniform for both direct and back scattering. However, the parameters such as depth $d(x)$, reflectance ρ, and spectral response S_c are ignored, limiting the true powers of restoration. Towards this, we propose to use revised image formation as shown in Equation 5 in two folds: restoration of degraded underwater images and synthetic data generation. Towards learning restoration, we consider depth as a clue in DepthCue. Towards synthetic data generation, we generate degraded observations (synthetic data) with corresponding ground-truth information [9] to facilitate learning-based restoration.

$$I(x) = J(x)t(x) + A(1 - t(x)) \tag{3}$$

where $J(x)$ is true scene radiance, $t(x)$ is the transmission and A is the veiling light. The transmission map $t(x)$ through the water medium is given by [40],

$$t(x) = e^{-\beta_\lambda d(x)} \tag{4}$$

$$I(x) = J(x)e^{-\beta_c^D(v_D)d(x)} + V_c^\infty(1 - e^{\beta_c^B(v_B)d(x)}) \tag{5}$$

where $v_D = \{d(x), \rho, E, S_c, \beta\}$ and $v_B = \{E, S_c, \beta, b\}$. Here $d(x)$ is the depth, ρ is the reflectance of each object in the scene, S_c is the spectral response of the camera, E is the spectral irradiance of the scene, b is the scattering coefficient and β is beam attenuation coefficient.

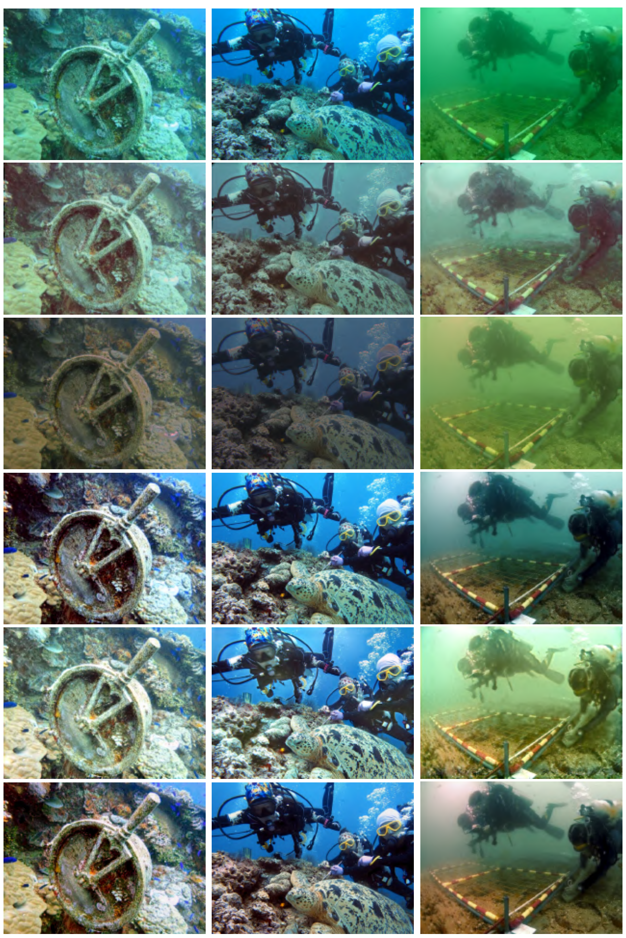

Figure 3: Restoration with learning based methods on UIEB [27] dataset. 1^{st} row shows input images, 2^{nd} row shows results from CWR method [18], 3^{rd} row shows results from UWCNN method [4], 4^{th} row shows results from WaveNet method [35], 5^{th} row shows results from AquaGAN method [8]. Last row shows results of DepthCue, restoration of color and contrast information appears realistic and natural.

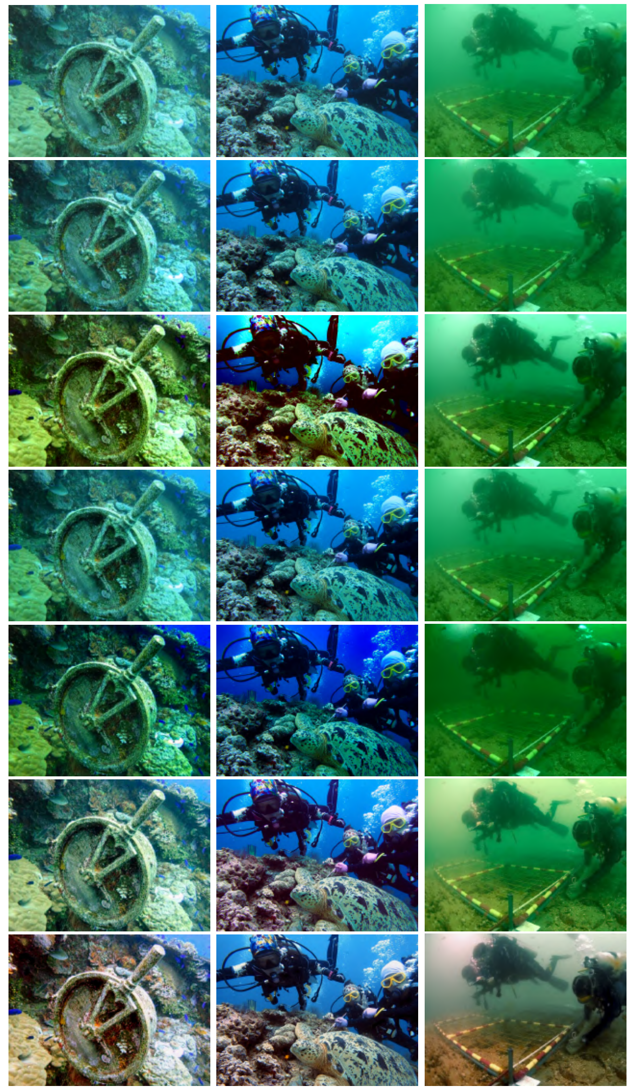

Figure 4: Restoration with non-learning based methods on UIEB [27] dataset. 1^{st} row shows input images, 2^{nd} row shows results from DCP method [19], 3^{rd} row shows results from MIP method [5], 4^{th} row shows results from RoWS method [6], 5^{th} row shows results from UDCP method [13], 6^{th} row shows results from ULAP method [36]. Last row shows results of DepthCue, restoration of color and contrast information appears realistic and natural.

Hou et al. [21] [22] measure the absorption and attenuation coefficients, particle size distribution, and volume scattering function using in-situ optical instruments, and are infeasible in real-time. Wang et al. [38] propose to estimate attenuation coefficients with respect to high contrast region. High contrast region is considered as a priori information to determine other parameters of the model. Chaing et al. [7] segment foreground and background to determine the presence of artificial source of light during the capture. Galdran et al. [15] estimate background light considering maximum value in red channel. Drews et al. [12] and Simon et al. [14] assume, the red channel attenuates faster, and is not sufficient information to determine the background light. They extend the work, to estimate minimum of green and blue channels, and consider it as priori.

Liu et al. [28] estimate priors (atmospheric light and transmission map) iteratively. Aupendu kar et al. [26] propose to use recurrent neural networks with iterative framework to de-haze an underwater image. Zhang et al. [41] propose to dehaze an image with transmission map using GAN framework. They minimize the combination of perceptual loss and Euclidean loss during training. However, perceptual and euclidean loss fail to exploit the true colors, contrast, and texture information in restoration process. Towards this, we propose to combine MSE and SSIM for restoring true colors, constrast and structural information along with texture.

We intend to perform restoration considering depth as a clue and our contributions are:

- We propose a learning-based framework towards restoration of degraded underwater images considering depth as a clue and term it as DepthCue.
- We propose to estimate the depth of underwater scene $d(x)$ with learning based techniques, and use the same as a clue towards restoration.
- We propose a combinational loss function to restore the true colors, contrast and texture information of degraded underwater images.
- We demonstrate the results of restoration using synthetic and real datasets to show the generalisability of the proposed model. We compare the quality of restoration with state-of-the-art techniques both qualitatively and quantitatively.
- We extend the usability of the proposed framework on dehazing as an objective.

In Section 2, we discuss the proposed methodology (DepthCue) for restoration of underwater images. We discuss the results of the proposed methodology in Section 3 and compare the same with state-of-the-art techniques. We present conclusion remarks in Section 4.

2. DepthCue: Restoration of underwater images using monocular depth as a clue

The scenarios such as hazy, foggy and smoggy in above water and underwater limits the underlying details of the scene. However, underwater scenario comes with additional challenges with water medium being the primary hindrance.

Figure 5: Restoration with learning and non-learning based methods on synthetic dataset, 1^{st} row shows input images, 2^{nd} and 3^{rd} row shows results of non-learning based techniques, 2^{nd} row shows results from ULAP [36], 3^{rd} row shows results from UDCP [13], 4^{th} to 7^{th} row corresponds to results from learning based methods, 4^{th} row shows results from WaveNet [35], 5^{th} row shows results from CWR [18], 6^{th} row shows results from AquaGAN [8], 7^{th} row shows results of the DepthCue (recovery of color and contrast is consistent throughout the scene), last row depicts the corresponding ground-truth images.

Typically, human brain perceives depth based on stereo vision. The position of eyes in human beings facilitates to perceive the width, height and depth of an object for determining the relative distance of each object in the scene. The information about relative distances of the object in the scene supports us in finding object size, color, texture and distance depending on the visibility of the scene. Experiments conducted in [3] clearly shows amount of degradation in underwater images is sensitive to depth.

Towards this, we propose a variant of encoder decoder architecture, DepthCue and introduce depth as a clue at different scales during restoration as shown in Figure 2. We introduce encoder and decoder modules with asymmetric skip connections in the proposed DepthCue.

At encoder we downsample the input by a factor of 2 in each step. We estimate depth by using a pre-trained model as given by authors in [16], the estimated depth acts as pseudo attention at each scale for the decoder. We intuitively use hierarchical depth as a pseudo attention for improving quality of restoration. From literature [42] we infer, receptive fields in the convolutional layers are learning local features at different scales. Typically, the consistency in visual appearance of the object across different scales is not ensured. With this intuition we downscale depth at different scales and interpret the scene in varying scales. Each scale will facilitate decoder to seek additional information about the scene through depth maps and facilitate restoration of underwater images.

Reconstruction at the original resolution is challenging at the decoder. Towards this, we propose to include corresponding upsampling blocks at the decoder part of DepthCue. Depth is provided as a clue at every scale of up-sampling block. Each up-sampling block includes a bottle neck layer followed by a deconvolutional layer for densifying the input. Features at corresponding scales are concatenated in encoder- decoder and are passed through convolutional block to restore the degraded underwater images. From literature [32] we infer, asymmetric nature of encoder-decoder architecture increases the capacity of the network. Unlike U-Net [33], we exploit asymmetric nature in proposed DepthCue for improved restoration.

Most of the architectures for restoration of underwater images include either MSE with L_2 and L_1 norm and SSIM as loss functions. However, images captured in underwater suffer from color loss, lower dynamic range and different types of degradations. Towards this, we propose a combinational loss function with MSE and SSIM to exploit the details of color, contrast and structure as shown in Section 2.1.

2.1. Proposed Loss Function

In this section, we emphasise on the combinational loss function proposed towards restoration of degraded underwater images. Since our focus is to perform restoration we compute pixel wise difference between the groundtruth image (Z) and the restored image $(\hat{Z})$. We propose to combine the advantages of MSE and SSIM loss functions for restoration of underwater images. Mean Square Error (MSE) loss helps to preserve the sharpness whereas SSIM loss facilitates restoration of lost contrast, texture and luminance of the degraded image. We propose the combination of MSE and SSIM loss function as shown in Equation 6 for restoration of overall aesthetics of an image.

$$Loss function = \alpha * MSE + (1-\alpha) * (1-SSIM) \quad (6)$$

where α is scaling factor. We consider $\alpha = 0.5$ after experimentating with different combinations for the proposed loss function.

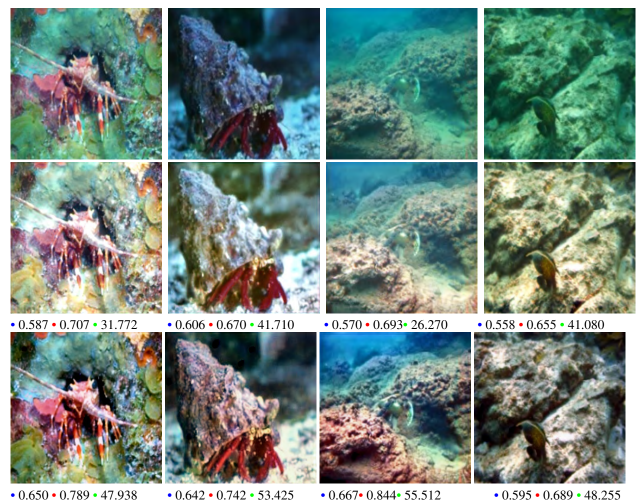

Figure 6: Shows additional results of proposed methodology (Blue, Red and Green dots indicate UCIQE, UIQM and CCF scores respectively) with quantitative scores on EUVP [24] and UFO-120 [23] datasets, 1^{st} and 2^{nd} column shows the results on EUVP [24] dataset in comparison with the authors in [8], 3^{rd} and 4^{th} column shows the results on UF0-120 [23] dataset in comparison with authors in [8], 1^{st} row shows input images, 2^{nd} row shows results of the authors in [8], 3^{rd} row shows the results of DepthCue.

3. Results and Discussions

In this section, we present the results of proposed methodology (DepthCue) both qualitatively and quantitatively. We demonstrate the results of restoration on real, and synthetic underwater images using UCIQE [39], UIQM [30] and CCF [37] as no-reference quantitative metrics. We consider real underwater images namely HICR [17] UIEB [27], EUVP [24] and UFO-120 [23] datasets and show proposed method outperforms for both learning and non-learning based restoration techniques. We demonstrate the results of proposed methodology on rendered synthetic

Table 1: Quantitative analysis using no-reference metrics for learning based restoration techniques on UIEB [27] and HICR [17] datasets (real underwater images). The 1^{st} column shows metrics for UWCNN method [4], 2^{nd} column shows metrics for CWR method [18], 3^{rd} column shows the metrics for WaveNet method [35], 4^{th} column shows the metrics for AquaGAN method [8], last column represents metrics for proposed methodology (DepthCue), Increase in performance of the proposed method (DepthCue) is shown in **bold**, ↑ indicates higher is better.

Method →	**UWCNN [4]**			**CWR [18]**			**WaveNet [35]**			**AquaGAN [8]**			**Ours**		
Metric → Dataset ↓	**UCIQE ↑**	**UIQM ↑**	**CCF ↑**	**UCIQE ↑**	**UIQM ↑**	**CCF ↑**	**UCIQE ↑**	**UIQM ↑**	**CCF ↑**	**UCIQE ↑**	**UIQM ↑**	**CCF ↑**	**UCIQE ↑**	**UIQM ↑**	**CCF ↑**
HICRD1	0.4464	0.6152	16.8232	0.4790	0.7011	18.5331	0.5209	0.6971	26.6790	0.4626	0.6513	23.9280	**0.5538**	**0.7125**	**31.0825**
HICRD2	0.4375	0.5899	15.5564	0.4696	0.6848	6.8810	0.5207	**0.7019**	23.5913	0.4231	0.6189	18.9437	**0.5344**	0.6886	**27.7158**
HICRD98	0.4793	0.6340	19.1321	0.4964	0.7110	19.7497	0.5259	0.6834	26.3643	0.4790	0.6530	25.8190	**0.5576**	**0.7088**	**31.5047**
HICRD99	0.4679	0.6263	18.3105	0.4936	0.7123	19.2059	0.5107	0.6781	25.2536	0.4784	0.6504	25.6575	**0.5574**	**0.7073**	**31.7491**
HICRD196	0.4578	0.6034	17.1228	0.4856	0.6903	18.2019	0.5317	0.6908	26.0363	0.5112	0.6855	26.2358	**0.5682**	**0.7095**	**30.9263**
HICRD197	0.4503	0.5940	17.0316	0.4872	0.6858	18.9455	0.5328	0.6826	27.2065	0.5112	0.6809	26.0945	**0.5629**	**0.7043**	**30.3089**
HICRD200	0.4587	0.6099	18.0332	0.4975	0.7017	19.8286	0.5442	**0.7174**	29.0405	0.5036	0.6692	26.5976	**0.5585**	0.7129	**30.5241**
UIEB 41	0.4912	0.6230	16.3341	0.5261	0.6037	21.1487	0.6449	0.7596	**56.6566**	0.5698	0.7097	32.6952	**0.6527**	**0.7623**	48.8777
UIEB 44	0.4750	0.6075	13.9857	0.5402	0.6528	21.1381	0.6617	0.8739	32.9983	0.6430	0.8241	38.3628	**0.6714**	**0.8803**	**40.3149**
UIEB 104	0.4105	0.2992	5.72060	0.4617	0.4598	14.4744	0.5805	**0.5068**	16.8709	0.5116	0.4955	10.9048	**0.5870**	0.4776	**20.9319**
UIEB 105	0.4329	0.3298	11.7471	0.5377	0.5788	14.8242	0.6293	**0.6522**	31.1855	0.5540	0.5832	26.5939	**0.6316**	0.6041	**31.5213**
UIEB 15603	0.4219	0.2180	5.4076	0.4889	0.4802	9.2080	**0.5707**	0.4058	11.3796	0.5019	0.3631	44.0622	0.5463	**0.4727**	**15.9781**
UIEB 15738	0.4595	0.2130	6.1780	0.5101	0.4249	10.2503	**0.6052**	0.4329	17.1607	0.4947	0.2766	11.0858	0.5983	**0.5199**	**19.5094**

underwater images using PSNR and SSIM as reference based quantitative metrics and show the proposed method (DepthCue) outperforms for both learning and non-learning based restoration methods. We further show the generalisability of the DepthCue considering dehazing as one of the usecases.

We train the proposed architecture on Nvidia DGX Tesla V100 for 500 epochs using Adam optimiser with $lr = 0.0002$, $beta1 = 0.5$ and $beta2 = 0.99$. We develop the proposed algorithm on Python (v3.8) and PyTorch framework. We use the proposed combinational loss function, more specifically MSE and SSIM for restoration of lost colors, contrast and structure using L_2 norm. We consider rendered synthetic underwater images as given by authors in [10] to train the proposed architecture (DepthCue). We consider a total of 4160 rendered images for training and 1040 images for testing.

In particular, we demonstrate the results of proposed methodology (DepthCue) in comparison with learning and non-learning based restoration methods on HICRD [17], UIEB [27], EUVP [24] and UFO-120 [23] datasets. We show the results of learning based restoration methods visually in Figure 8, Figure 3, and Figure 6. The corresponding no-reference quantitative scores are shown in Table 1. We show the results of non-learning based restoration methods visually in Figure 7 and Figure 4. The corresponding no-reference quantitative scores is shown in Table 2. We validate the results of proposed methodology on synthetic underwater images across different tints and show the same visually in Figure 5. The corresponding quantitative scores for the same are shown in Table 3. We demonstrate additional results on EUVP [24] and UFO-120 [23] datasets to prove depth as a clue improves restoration as shown in Figure 6.

Unlike other SOTA techniques, in Figure 3 and 4, we observe the restoration of color and contrast information appears realistic and natural with the proposed methodology. It is apparent from Figure 8, by providing depth parameter as additional information improves the restoration. We see in Figure 8, removal of tint, recovery of color and contrast is consistent throughout the scene with the proposed methodology (DepthCue), however in SOTA techniques the quality of restoration is not consistent. To validate the performance of proposed methodology, we exhibit results of restoration on synthetically rendered underwater images considering indoor scenes and color charts. In Figure 5, we observe the lost colors, contrast and other information in the scene is very close to ground-truth images with DepthCue.

Table 2: Quantitative analysis for non-learning based restoration techniques using no-reference metrics. The 1^{st} column shows metrics obtained using HICRD dataset, 2^{nd} column shows metrics obtained using UIEB dataset, rows depicts non-learning based methods, last row corresponds to results of the proposed methodology (DepthCue).

Datasets →	HICR Dataset [17]			UIEB Dataset [27]		
Metric → Methods ↓	UCIQE ↑	UIQM ↑	CCF ↑	UCIQE ↑	UIQM ↑	CCF ↑
MIP	0.45044	0.71749	13.72548	0.62227	0.75021	60.78405
UDCP	0.49238	0.78010	24.5511	0.54984	0.65634	39.69742
ULAP	0.45764	0.73254	26.36227	0.59953	0.61758	44.93024
RoWS	0.45525	0.65258	14.0895	0.55997	0.54743	38.78192
Ours	**0.52654**	**0.70153**	**29.7700**	**0.61297**	**0.61954**	**29.04847**

3.1. Applications

We extend the study on dehazing methods to show the generalisability of the model. Dehazing methods are one of the modules in underwater image restoration. We demonstrate the results of restoration on hazy images as shown in Figure 9. From the Figure 9 it is evident that, encompassing the image formation model in deep learning frameworks

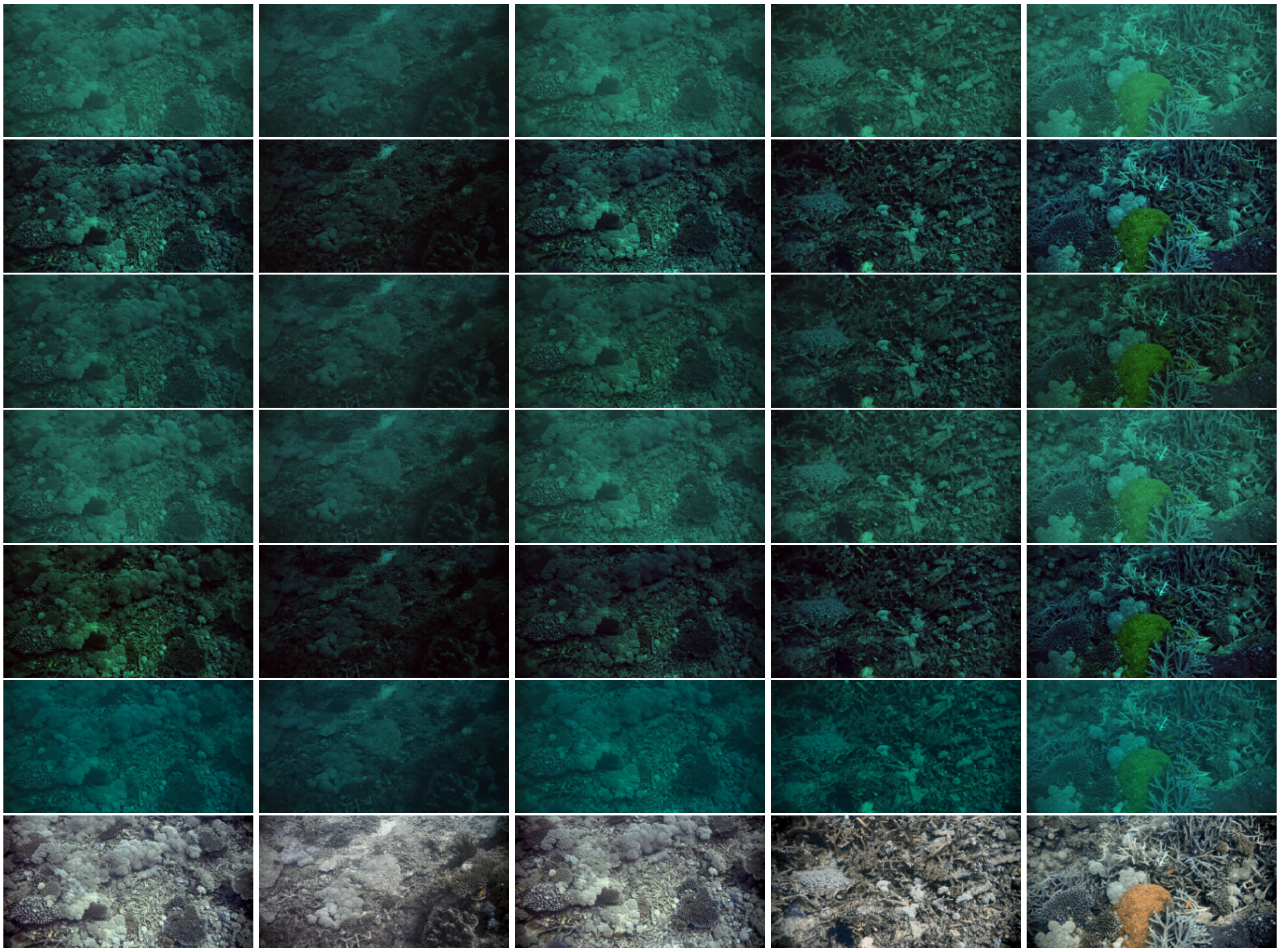

Figure 7: Restoration with non-learning based methods on HICRD dataset [17]. 1^{st} row shows input images, 2^{nd} row shows results from DCP method [19], 3^{rd} row shows results from MIP method [5], 4^{th} row shows results from RoWS method [6], 5^{th} row shows results from UDCP method [13], 6^{th} row shows results from ULAP method [36], last row shows results of the DepthCue (recovery of color and contrast is consistent throughout the scene).

Table 3: Quantitative analysis for learning and non-learning based techniques with reference based metrics on synthetic dataset. Columns(left to right) depicts methods. Last column shows the results of proposed methodology. We show the mean of PSNR and SSIM scores for the synthetic test dataset in last column.

Methods → Metrics ↓	**Input**	**DCP [19]**	**MIP [5]**	**UDCP [13]**	**ULAP [36]**	**RoWS [6]**	**UWCNN [4]**	**CWR [18]**	**WaveNet [35]**	**AquaGAN [8]**	**Ours (DepthCue)**
PSNR	9.3370	8.9075	9.3871	7.8232	10.3902	9.1841	12.4719	13.80176	13.5374	13.6382	34.1051
SSIM	0.42019	8.9075	0.2252	0.2252	0.4931	0.3970	0.6224	0.59704	0.6521	0.6374	0.9594

will provide solutions to other sub problems like Dehazing, Denoisiong and Deblurring.

4. Conclusions

In this work, we have restored the underwater images by incorporating principles of the image formation model in deep neural networks. We have considered the degraded underwater image and its corresponding depth as clue for training the proposed architecture (DepthCue). We have proposed a variant of encoder-decoder architecture (DepthCue) and introduced depth information as a clue at every scale at the decoder during restoration. We have shown, the proposed method outperforms in comparison with state-of-the-art techniques on benchmark datasets both qualitatively and quantitatively. We have demonstrated the generalizability of the model on dehazing as an application.

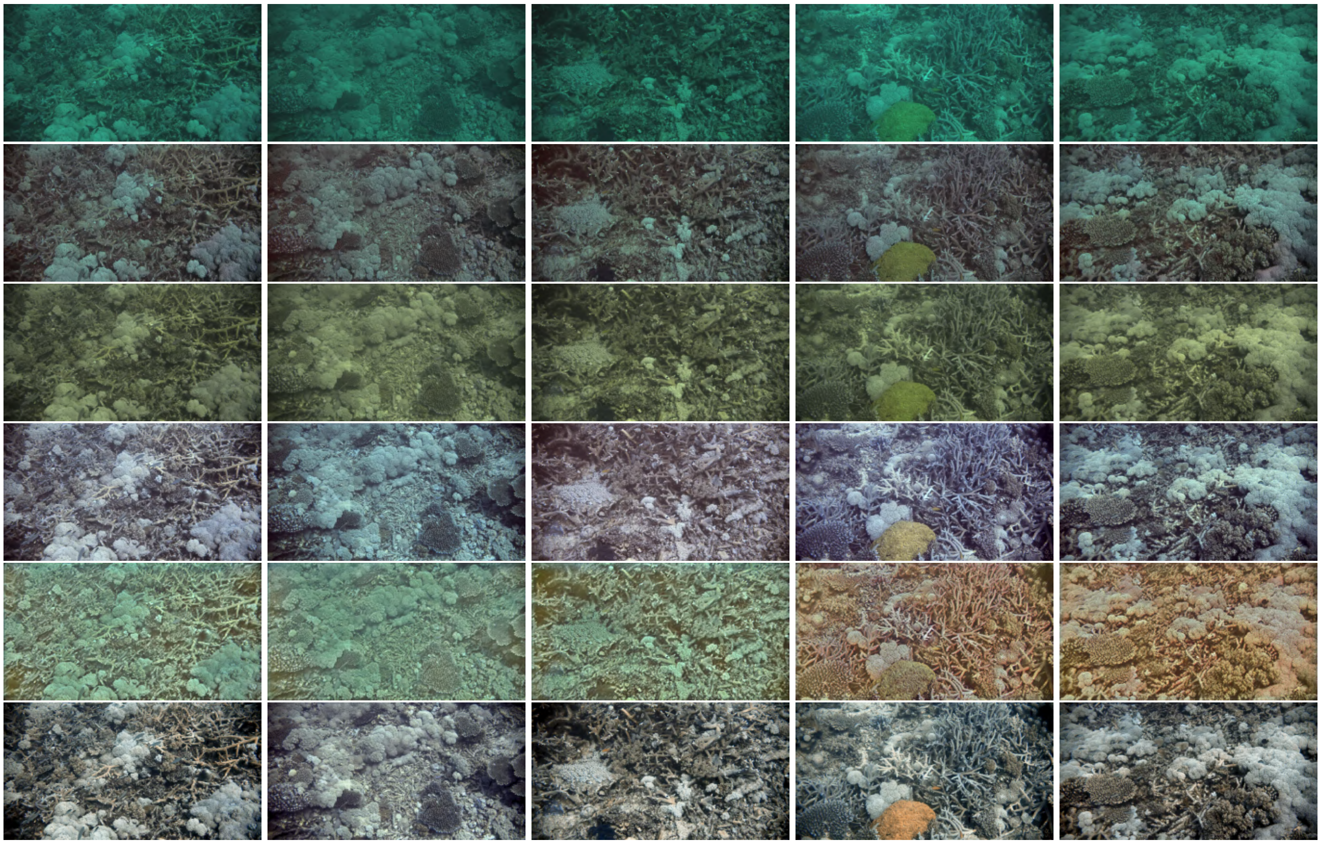

Figure 8: Restoration with learning based methods on HICRD [17] dataset. 1^{st} row shows input images, 2^{nd} row shows results from CWR method [18], 3^{rd} row shows results from UWCNN method [4], 4^{th} row shows results from WaveNet method [35], 5^{th} row shows results from AquaGAN method [8], last row shows results of the DepthCue (recovery of color and contrast is consistent throughout the scene).

Figure 9: Restoration on hazy images. 1^{st} row shows the input images, 2^{nd} row depicts the results of dehazed images using DepthCue.

5. Acknowledgement

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References

[1] Jarina Ahamed, Pg Emeroylariffion Abas, and Liyanage De Silva. Review of underwater image restoration algorithms. *IET Signal Processing*, 13, 08 2019.

[2] Derya Akkaynak and Tali Treibitz. A revised underwater image formation model. In *Proceedings of the IEEE Confer-*

ence on Computer Vision and Pattern Recognition (CVPR), June 2018.

[3] Derya Akkaynak and Tali Treibitz. Sea-thru: A method for removing water from underwater images. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.

[4] Saeed Anwar, Chongyi Li, and Fatih Porikli. Deep underwater image enhancement, 2018.

[5] Nicholas Carlevaris-Bianco, Anush Mohan, and Ryan M. Eustice. Initial results in underwater single image dehazing. In *OCEANS 2010 MTS/IEEE SEATTLE*, pages 1–8, 2010.

[6] Liu Chao and Meng Wang. Removal of water scattering. In *2010 2nd International Conference on Computer Engineering and Technology*, volume 2, pages V2–35–V2–39, 2010.

[7] John Y. Chiang and Ying-Ching Chen. Underwater image enhancement by wavelength compensation and dehazing. *IEEE Transactions on Image Processing*, 21(4):1756–1769, 2012.

[8] Chaitra Desai, Badduri Sai Sudheer Reddy, Ramesh Ashok Tabib, Ujwala Patil, and Uma Mudenagudi. Aquagan: Restoration of underwater images. In *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 295–303, 2022.

[9] Chaitra Desai, Ramesh Ashok Tabib, Sai Sudheer Reddy, Ujwala Patil, and Uma Mudenagudi. Rendering of synthetic underwater images towards restoration. In *SIGGRAPH Asia 2021 Posters*, SA '21 Posters, New York, NY, USA, 2021. Association for Computing Machinery.

[10] Chaitra Desai, Ramesh Ashok Tabib, Sai Sudheer Reddy, Ujwala Patil, and Uma Mudenagudi. Ruig: Realistic underwater image generation towards restoration. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, pages 2181–2189, June 2021.

[11] C S Dikshith, Sameeksha M Vernekar, Chaitra Desai, Ujwala Patil, and Uma Mudenagudi. Restoration of degraded underwater images with attenuation coefficients as a clue. *IOP Conference Series: Materials Science and Engineering*, 1187(1):012014, sep 2021.

[12] P. Drews Jr, E. do Nascimento, F. Moraes, S. Botelho, and M. Campos. Transmission estimation in underwater single images. In *2013 IEEE International Conference on Computer Vision Workshops*, pages 825–830, 2013.

[13] P. Drews Jr, E. do Nascimento, F. Moraes, S. Botelho, and M. Campos. Transmission estimation in underwater single images. In *2013 IEEE International Conference on Computer Vision Workshops*, pages 825–830, 2013.

[14] Simon Emberton, Lars Chittka, and Andrea Cavallaro. Hierarchical rank-based veiling light estimation for underwater dehazing. In Mark W. Jones Xianghua Xie and Gary K. L. Tam, editors, *Proceedings of the British Machine Vision Conference (BMVC)*, pages 125.1–125.12. BMVA Press, September 2015.

[15] Adrian Galdran, David Pardo, Artzai Picón, and Aitor Alvarez-Gila. Automatic red-channel underwater image restoration. *Journal of Visual Communication and Image Representation*, 26:132–145, 2015.

[16] Clément Godard, Oisin Mac Aodha, and Gabriel J. Brostow. Unsupervised monocular depth estimation with left-right consistency. In *CVPR*, 2017.

[17] Junlin Han, Mehrdad Shoeiby, Tim Malthus, Elizabeth Botha, Janet Anstee, Saeed Anwar, Ran Wei, Ali Armin, Hongdong Li, and Lars Petersson. Underwater image restoration via contrastive learning and a real-world dataset, 06 2021.

[18] Junlin Han, Mehrdad Shoeiby, Tim Malthus, Elizabeth Botha, Janet Anstee, Saeed Anwar, Ran Wei, Lars Petersson, and Mohammad Ali Armin. Single underwater image restoration by contrastive learning, 2021.

[19] Kaiming He, Jian Sun, and Xiaoou Tang. Single image haze removal using dark channel prior. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1956–1963, 2009.

[20] Deepti Hegde, Chaitra Desai, Ramesh Tabib, Ujwala B. Patil, Uma Mudenagudi, and Prabin Kumar Bora. Adaptive cubic spline interpolation in cielab color space for underwater image enhancement. *Procedia Computer Science*, 171:52–61, 2020. Third International Conference on Computing and Network Communications (CoCoNet'19).

[21] Weilin Hou, Deric J. Gray, Alan D. Weidemann, Georges R. Fournier, and J. L. Forand. Automated underwater image restoration and retrieval of related optical properties. In *2007 IEEE International Geoscience and Remote Sensing Symposium*, pages 1889–1892, 2007.

[22] Weilin Hou, Alan D. Weidemann, Deric J. Gray, and Georges R. Fournier. Imagery-derived modulation transfer function and its applications for underwater imaging. In Andrew G. Tescher, editor, *Applications of Digital Image Processing XXX*, volume 6696, pages 707 – 714. International Society for Optics and Photonics, SPIE, 2007.

[23] Md Jahidul Islam, Peigen Luo, and Junaed Sattar. Simultaneous Enhancement and Super-Resolution of Underwater Imagery for Improved Visual Perception. In *Robotics: Science and Systems (RSS)*, Corvalis, Oregon, USA, July 2020.

[24] Md Jahidul Islam, Youya Xia, and Junaed Sattar. Fast underwater image enhancement for improved visual perception. *IEEE Robotics and Automation Letters (RA-L)*, 5(2):3227–3234, 2020.

[25] J. Jaffe. Corrections to "underwater optical imaging: The past, the present, and the prospects" [j. s. jaffe, ieee j. ocean. eng., doi: 10.1109/joe.2014.2350751]. *IEEE Journal of Oceanic Engineering*, 40(3):754–754, July 2015.

[26] Aupendu Kar, Sobhan Kanti Dhara, Debashis Sen, and Prabir Kumar Biswas. Transmission map and atmospheric light guided iterative updater network for single image dehazing, 2020.

[27] C. Li, C. Guo, W. Ren, R. Cong, J. Hou, S. Kwong, and D. Tao. An underwater image enhancement benchmark dataset and beyond. *IEEE Transactions on Image Processing*, 29:4376–4389, 2020.

[28] Yang Liu, Jinshan Pan, Jimmy Ren, and Zhixun Su. Learning deep priors for image dehazing. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.

[29] C. D. (ed.) (2022) Mobley. The oceanic optics book. dartmouth, ns, canada, international ocean colour coordinating group (ioccg). (924).

[30] K. Panetta, C. Gao, and S. Agaian. Human-visual-system-inspired underwater image quality measures. *IEEE Journal of Oceanic Engineering*, 41(3):541–551, 2016.

[31] Zeba Patel, Chaitra Desai, Ramesh Ashok Tabib, Medha Bhat, Ujwala Patil, and Uma Mudengudi. Framework for underwater image enhancement. *Procedia Computer Science*, 171:491–497, 2020. Third International Conference on Computing and Network Communications (CoCoNet'19).

[32] Kuldeep Purohit, Anshul Shah, and A. N. Rajagopalan. Unfolding a blurred image, 2022.

[33] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. *CoRR*, abs/1505.04597, 2015.

[34] Y. 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 I–I, 2004.

[35] Prasen Kumar Sharma, Ira Bisht, and Arijit Sur. Wavelength-based attributed deep neural network for underwater image restoration, 2021.

[36] Wei Song, Yan Wang, Dongmei Huang, and Dian Tjondronegoro. *A Rapid Scene Depth Estimation Model Based on Underwater Light Attenuation Prior for Underwater Image Restoration*, pages 678–688. 09 2018.

[37] Yan Wang, Na Li, Zongying Li, Zhaorui Gu, Haiyong Zheng, Bing Zheng, and Mengnan Sun. An imaging-inspired no-reference underwater color image quality assessment metric. *Computers & Electrical Engineering*, 70:904–913, 2018.

[38] Yan Wang and Bo Wu. Fast clear single underwater image. In *2010 International Conference on Computational Intelligence and Software Engineering*, pages 1–4, 2010.

[39] M. Yang and A. Sowmya. An underwater color image quality evaluation metric. *IEEE Transactions on Image Processing*, 24(12):6062–6071, 2015.

[40] He Zhang, Vishwanath Sindagi, and Vishal M. Patel. Joint transmission map estimation and dehazing using deep networks. *IEEE Transactions on Circuits and Systems for Video Technology*, 30(7):1975–1986, 2020.

[41] He Zhang, Vishwanath Sindagi, and Vishal M. Patel. Joint transmission map estimation and dehazing using deep networks. *IEEE Trans. Cir. and Sys. for Video Technol.*, 30(7):1975–1986, July 2020.

[42] Yulun Zhang, Yapeng Tian, Yu Kong, Bineng Zhong, and Yun Fu. Residual dense network for image restoration. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 43(7):2480–2495, 2021.