Deep Underwater Image Restoration and Beyond

Akshay Dudhane, *Student Member, IEEE*, Praful Hambarde, Prashant Patil, and Subrahmanyam Murala, *Member, IEEE*

***Abstract*—Underwater image restoration is a challenging problem due to the multiple distortions. Degradation in the information is mainly due to the 1) light scattering effect 2) wavelength dependent color attenuation and 3) object blurriness effect. In this letter, we propose a novel end-to-end deep network for underwater image restoration. The proposed network is divided into two parts *viz.* channel-wise color feature extraction module and dense-residual feature extraction module. A custom loss function is proposed, which preserves the structural details and generates the true edge information in the restored underwater scene. Also, to train the proposed network for underwater image enhancement, a new synthetic underwater image database is proposed. Existing synthetic underwater database images are characterized by light scattering and color attenuation distortions. However, object blurriness effect is ignored. We, on the other hand, introduced the blurring effect along with the light scattering and color attenuation distortions. The proposed network is validated for underwater image restoration task on real-world underwater images. Experimental analysis shows that the proposed network is superior than the existing state-of-the-art approaches for underwater image restoration.**

***Index Terms*—Deep learning, image restoration, light scattering, underwater haze.**

I. Introduction

THE low visibility (due to scattering of light), color shift and blurriness degrades the quality of images captured by the visual camera under water [3], [8]. Thus, visibility improvement in the underwater images is the foremost task before processing it through high-level vision algorithms. This brings considerable attention of the research community to work on underwater image restoration. Initially, researchers make use of additional information like multiple images of the same scene [30], polarizing filters [37] etc. for underwater image restoration. Approaches in single underwater image restoration are divided into non-physical model-based approaches and physical model-based approaches. Non-physical model-based approaches consists of multi-scale fusion strategy [1], two-step approach (color correction followed by contrast enhancement) [14] etc. Physical model-based approaches comprise of inverse imaging i.e. estimation of the unknown parameters of the degradation model for restoration of the underwater image. He *et al.* [18] have proposed the dark channel prior to estimate the unknown parameters of the atmospheric scattering model for image de-hazing. Chiang *et al.* [8] modified atmospheric scattering model to incorporate underwater distortions. They have proposed a wavelength-dependent compensation algorithm to reduce distortions in the underwater image. Drews *et al.* [9] have proposed an underwater dark channel prior to restore the underwater images. Peng *et al.* [34] proposed a generalized dark channel prior for underwater image restoration.

Manuscript received January 20, 2020; revised March 2, 2020; accepted March 31, 2020. Date of publication April 20, 2020; date of current version May 19, 2020. This work was supported by the DST-SERB, India, under Grant ECR/2018/001538. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Dezhong Peng. *(Corresponding author: Subrahmanyam Murala.)*

The authors are with the CVPR Lab, Electrical Engineering Department, IIT Ropar, Rupnagar 140001, India (e-mail: 2017eez0001@iitrpr.ac.in; 2018eez0001@iitrpr.ac.in; 2017eez0006@iitrpr.ac.in; subbumurala@iitrpr.ac.in).

This letter has supplementary downloadable material available at https://ieeexplore.ieee.org, provided by the authors.

Digital Object Identifier 10.1109/LSP.2020.2988590

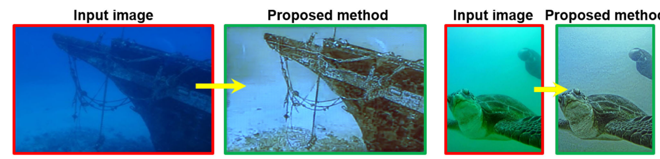

Fig. 1. Results of underwater images restored using the proposed approach.

Red color has the longest wavelength, it attenuates faster when compared with blue and green color [6]. Galdran *et al.* [16] proposed a Red Channel method for underwater image restoration. They recovered the contrast of the underwater image by restoring colors associated with the shorter wavelengths. Further, Retinex model is proposed by Fu *et al.* [15] for underwater image restoration. Peng *et al.* [35] restored underwater image by incorporating depth information in underwater image formation model. They estimated underwater image depth based on the concept of light absorption and blurriness in an underwater image. Berman *et al.* [5] proposed an underwater image enhancement approach by considering multiple spectral profiles of different water types. Zhang *et al.* [39] proposed multi-scale Retinex algorithm to reduce distortion in underwater images. In [2], author proposed multi-scale fusion strategy for underwater image enhancement. Further, Zhou *et al.* [40] have utilized color-line prior for underwater image enhancement.

Advancement in deep learning significantly improved the performance of various computer vision tasks [7], [13], [28], [33]. A major hurdle in any learning-based approach is to have a large-scale training database. Thus, researchers make use of synthetic datasets to train the deep network for a particular task. Li *et al.* [27] have proposed a WaterGAN to generate synthetic underwater images. They used synthetically generated underwater images to train a two-stage deep network for underwater image enhancement. However, it is limited to specific underwater scenes. To overcome the unavailability of large-scale real-world training data, in [26], [32] authors made use of an unpaired learning approach. However, unpaired learning [26] is applicable to particular water type and is not generalized. Further, in [7], authors proposed a dark channel prior loss for optimization of the network parameters for underwater image

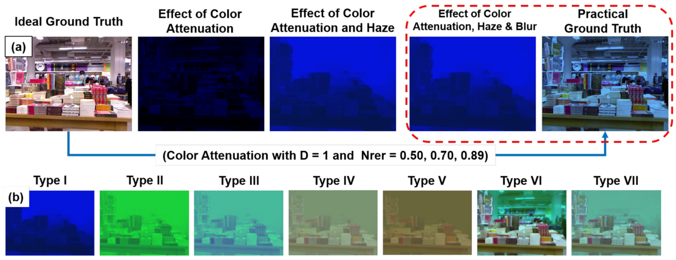

Fig. 2. Generation of synthetic underwater images. (a) Step-wise generation of synthetic images (b) Sample underwater image from each water Type.

enhancement and overcome the unavailability of the paired training data.

Even though existing deep learning-based approaches enhance the underwater image contrast and improve the visibility in underwater images, they fail in case of extreme distortions. The reason behind this is existing deep learning-based approaches use synthetic underwater image and respective distortion less image as a ground truth. Thus, in this case, objective of the deep network is to achieve complete restoration of the synthetic underwater image. However, in a real-world scenario, complete restoration of the underwater image is highly impossible. Also, it does not look perceptually pleasant when there is no underwater scene effect. Also, it is observed that most of the existing approaches are effective for a particular water type, and there is no generalized approach that could work in multiple water types and various levels of distortions. Thus, there is scope to design a generalized approach that will enhance both coastal as well as shallow underwater images and which will be applicable to different levels of distortions. Considering the above observations, in this letter, an End-to-End Underwater Image Restoration Network is proposed. Also, we propose a novel approach to generate a pair of synthetic underwater images with their respective practically achievable reference images (ground truth). Contributions of the work are listed as follows:

1) A novel approach to generate a pair of synthetic underwater images with their respective practically achievable reference images is proposed.
2) Large-scale synthetic underwater image database is created by considering different water types to train a deep network for underwater image enhancement.
3) A novel end-to-end network is proposed for underwater image restoration.

II. Proposed Approach for Synthetic Underwater Image Generation

In the existing literature, the underwater image databases [10], [23], [24] are publically available for research purpose. However, these databases are not useful for the training of deep networks for underwater image enhancement because of the fewer number of underwater images. Thus, the generation of large-scale synthetic underwater image database is essential to train a deep network for underwater image enhancement. In this direction, Li *et al.* [27] have proposed WaterGAN. It is observed that WaterGAN is limited to generate the specific type of underwater images. Further, Li *et al.* [25] have constructed a set of real-world underwater images and their respective reference images (not the actual ground truth). Recently, Anwar *et al.* [4] simulated the underwater images using an underwater image formation model. They considered only low visibility and color shift as an image quality degradation parameter and have not considered the blurriness effect. Thus, there is a lack of a large-scale synthetic underwater image database, which consists of all three types of distortions. In this letter, we propose a novel synthetic underwater image generation model and construct a large-scale database to train a deep network for underwater image enhancement task.

A. Proposed Underwater Image Formation Model

Process of synthetic underwater image formation is shown in Fig. 2(a). Following [8], the underwater image formation can be expressed as,

$$2U_\lambda(x) = \left(I_\lambda(x) \cdot \text{Nrer}\,(\lambda)^D\right) \cdot \text{Nrer}\,(\lambda)^{\beta\times d(x)} + A_\lambda \left(1 - \text{Nrer}\,(\lambda)^{\beta\times d(x)}\right) \quad (1)$$

where $U_\lambda(x)$ is the underwater image, $I_\lambda(x)$ is the scene radience at point x, Nrer(λ) is the normalized residual energy ratio and it depends on the wavelength of the light [8], D is a vertical depth under water, $d(x)$ is a horizontal depth at point x under water, β represents the attenuation factor, A_λ is the homogeneous global background light, and λ is the wavelength of the light for the red, green and blue channels.

In Eq. 1, factors Nrer$(\lambda)^D$ and Nrer$(\lambda)^{\beta\times d(x)}$ are responsible for the color shift and haze (low visibility) respectively in underwater image. Along with the color attenuation and low visibility, image blurriness is also observed in real-world underwater images. Thus, we applied guided image filter [17] to introduce object blurriness in synthetic underwater images. Thus, Eq. (1) can be reformulated as,

$$2U_\lambda(x) = \underset{y\in\Omega(x)}{\text{avg}} \left(\left(I_\lambda(y) \cdot \text{Nrer}\,(\lambda)^D\right) \cdot \text{Nrer}\,(\lambda)^{\beta\times d(x)}\right) + A_\lambda \left(1 - \text{Nrer}\,(\lambda)^{\beta\times d(x)}\right) \quad (2)$$

where, $\text{avg}_{y\in\Omega(\cdot)}$ is a guided image filtering on local region $\Omega(x)$. Here, in Eq. (2), Nrer$(\lambda)^{d(x)}$ is locally constant [8], [18] and thus, are out of the filtering operation.

B. Synthetic Underwater Image Database Generation

We make use of Eq. (2) to generate the synthetic underwater images. In Eq. (2), the scene depth map is unknown. Thus, we consider NYU RGB-D [38] database, which consists of 1449 indoor images and respective depth maps. In NYU RGB-D [38] database, horizontal depth $d(x)$ varies from 0.5 m to 15 m. Further, background light A_λ is considered between 0 to 1. We apply the guided filter of variance 1.2 to blur the generated image. With this setting, we have generated synthetic underwater images of seven different water Types, respective parameters are given in Table I. Sample synthetic underwater image from each water Type shown in Fig. 2(b). As discussed earlier, it is highly impossible to achieve complete restoration of underwater images. Thus, instead of stretching deep network for complete restoration task, we allow it to learn the practically achievable restoration. This process improves the underwater image restoration and is observed in ablation study (*given in supplementary material*). Thus, we generate a practically achievable reference image from the actual reference image. For ex. if D = 20, β=3,

TABLE I
PARAMETERS CONSIDERED WHILE GENERATING THE PROPOSED SYNTHETIC UNDERWATER IMAGE DATABASE

Type	Nrer(λ)	A_λ	D, β
I	0.01, 0.19, 0.89	0.02, 0.08, 0.89	20, 3
II	0.12, 0.89, 0.29	0.10, 0.82, 0.23	0.5, 5.5
III	0.01, 0.89, 0.49	0.28, 0.73, 0.61	0.1, 5.5
IV	0.75, 0.88, 0.87	0.35, 0.70, 0.60	0.5, 3
V	0.67, 0.73, 0.67	0.47, 0.58, 0.44	0.1, 3
VI	0.62, 0.61, 0.50	0.41, 0.40, 0.23	0.1, 2.2
VII	0.80, 0.96, 0.98	0.10, 0.90, 0.10	1, 1

Nrer = 0.01, 0.19, 0.89 are the parameters used to generate Type I synthetic underwater image then D = 1, β = 1, Nrer = 0.50, 0.70, 0.89 are used to generate less distorted practically achievable reference image. Fig. 2(a) shows the stepwise generation of synthetic underwater image and respective practically achievable reference image. Sample underwater image from each water Type is shown in Fig. 2(b).

III. PROPOSED UNDERWATER IMAGE ENHANCEMENT

The proposed approach to restore the underwater images is discussed in this Section. As discussed in Section I, distortion in images captured in the underwater medium is mainly due to the 1) light scattering effect, 2) wavelegnth dependent color attenuation and 3) object blurriness effect, which makes underwater images less informative. Thus, a strong learning algorithm is required to generate information from observed sparse data. With this observation, we make use of the conditional generative adversarial network (cGAN) [22] to reduce these distortions from underwater images and to enhance the details in the underwater image. cGAN consists of two networks, generator, and discriminator. Discriminator network proposed in [13] is utilized here to discriminate between generator output and ground truth. In this letter, we propose a novel generator network which is designed to tackle the distortions discussed above and to enhance the underwater image. Details are discussed in sub-sequent sections.

A. Proposed Generator Network Architecture

We propose a channel-wise dense-residual network as a generator for underwater image enhancement. The proposed network is divided into two parts *viz.* channel-wise feature extraction using depth-wise separable convolution filters followed by the dense-residual network. The proposed channel-wise feature extraction module is designed to extract the color relevant features. Whereas, Dense-Residual network is designed for underwater image de-hazing and de-blurring.

1) Channel-Wise Feature Extraction: As discussed in Section II.A, different wavelengths have different range of existence under water. Thus, to enhance the underwater images, it is essential to process each color channel separately. To the best of our knowledge, this is the first attempt in which color channels are separately processed for underwater image enhancement. Here, we claim that separately processing each color channel allows the deep network to learn what weight should be given to each color channel so that it could generate perceptually pleasant colors. Thus, we utilized the concept of depth-wise convolution filter [11], [12], [20] to extract channel-wise color features. Each color channel of input underwater image is processed through a separate convolution layer as shown in Fig. 3. Each convolution layer has 16 filters.

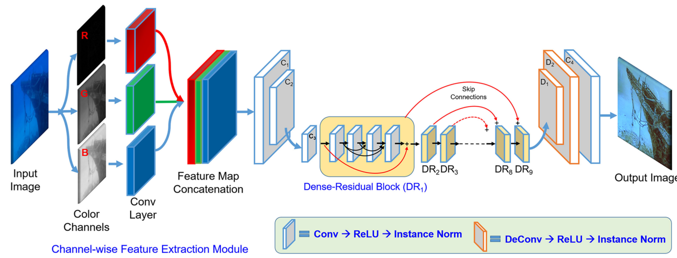

Fig. 3. Proposed network for underwater image restoration.

2) Dense-Residual Network: Deep networks can be trained efficiently when consisting of shorter connections between layers close to the input and those close to the output [19], [21]. This aspect of deep network inspired us to design a network using the principles of residual [19] and dense networks [21]. In this letter, we propose a dense-residual network for underwater image enhancement. The proposed dense-residual block is shown in Fig. 3. It consists of four convolution layers having a number of filters 32, 32, 64, 128 sequentially. Feature responses of these convolution layers are densely connected. We make use of feature map concatenation to share the features within the Dense-Residual block. Feature map concatenation increases variation in the input of subsequent layers by concatenating features learned by previous layers. Thus, it improves the efficiency of the model for a given task. Further, we utilized identity mapping and element-wise added input features with the output of dense learning.

The proposed network comprises nine dense-residual blocks, as shown in Fig. 3. Along with the feature learning, there is a great importance of sharing of the low-level features across the network for proper recovery of structural details in the restored images [22]. Thus, in the proposed network, skip connections are employed to share the initial feature maps across the network to keep alive the structural information. Each skip connection does an element-wise feature map summation instead of feature map concatenation. Response of the dense-residual blocks is processed through the de-convolution layer and passes through a output convolution layer to obtain the enhanced underwater image. Fig. 3 shows the process of underwater image enhancement using the proposed network.

B. Training Details

Training dataset comprise synthetically generated underwater images and their respective practically achievable ground truth (shown in Fig. 2). We have generated 1449 synthetic underwater images using each set of coefficients as given in Table I. Thus, in total, the proposed synthetic underwater image database consists of 1449 $\times$ 7 = 10,143 images and respective ground truths. It is divided into training (80%) and testing (20%) set. Hyper-parameters like learning rate = 0.0001, # epochs = 200 are considered. To generate the true edge information and to preserve the structural details in the recovered images, we strengthen cGAN objective by incorporating edge and SSIM loss along with L_1 loss. Thus, loss function is,

$$\mathcal{L}(G, D) = \ell_{cGAN}(G, D) + \lambda_1 \cdot \ell_{L1}(G)$$

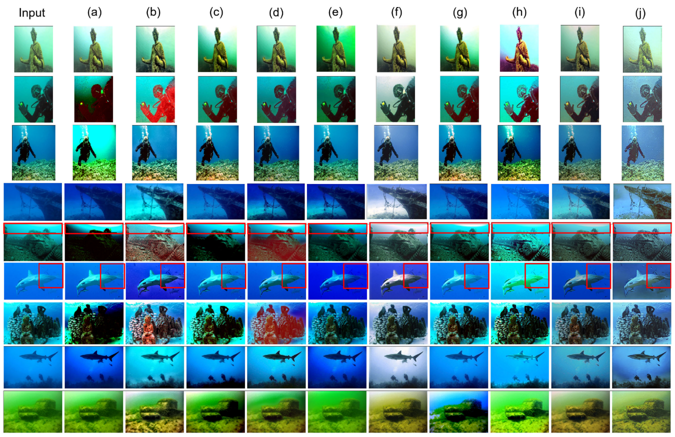

Fig. 4. Visual comparison between results of the proposed and existing (a) [6], (b) [1], (c) [36], (d) [16], (e) [9], (f) [2], (g) [35], (h) [34], (i) [25] methods and (j) the proposed method on real-world underwater images.

$$+ \lambda_2 \cdot \ell_{SSIM}(G) + \lambda_3 \cdot \ell_{Edge}(G) \quad (3)$$

where, $\ell_{cGAN}(G, D)$ conditional GAN loss, $\ell_{L1}, \ell_{SSIM}, \ell_{Edge}$ are traditional L1, SSIM and Edge loss respectively, and $\lambda_1 = \lambda_2 = 10$ and $\lambda_3 = 1$ are the loss weigthage.

IV. Results and Discussion

Here, we have discussed the validation of the proposed network for the underwater image restoration task.

A. Analysis on Real-World Underwater Images

To show the robustness of the proposed network, we have considered both highly distorted as well as minimal distorted real-world underwater images. Results of the proposed and existing methods on real-world underwater images are shown in Fig. 4 which shows that the proposed network outperforms the other existing methods for underwater image enhancement. Even though input underwater image is extremely distorted, restored underwater image using the proposed network does not undergo color distortion. Rather, the proposed network tries to improve the visibility in underwater images by generating perceptually pleasant colors. We give this credit to the proposed channel-wise feature extraction and use of practically achievable ground truth images to train the network. On the other side, existing approaches fail on extremely distorted underwater images and undergo serious color distortion.

Two no-reference quality measurement parameters UIQM [31] and BRISQUE [29] are considered for quantitative analysis of the proposed and existing methods on real-world underwater images. Table II depicts the performance comparison between the proposed and existing methods on real-world underwater images in terms of the no-reference evaluation parameters. Fig. 4 and Table II witnessed the superiority of the proposed network over existing methods for underwater image restoration.

B. Analysis on Synthetic Underwater Images

We have considered testing split of the synthetic underwater image database (discussed in Section III.B) for the quantitative analysis of the proposed network for the underwater image restoration task. SSIM, PSNR, CIEDE2000 are considered as an evaluation parameters. For ideal restoration, SSIM $= 1$, PSNR should be as high as possible and CIEDE2000 is as low as possible. Most of the existing approaches are evaluated only on a small set of real-world underwater images. Here, we have evaluated the performance of the proposed and existing approaches on large set of images (2028) and is given in Table III. Accuracy of the proposed network is far ahead of the existing methods, which show the robustness of the proposed approach for underwater image enhancement. Visual results of the proposed and existing methods on synthetic underwater images and additional real-world underwater images are given in the supplementary material.

TABLE II
Performance Evaluation of the Proposed and Existing Methods on Set of Underwater Images Shown in Fig. 4

Methods	Publication	UIQM ↑	BRISQUE ↓
Ancuti *et al.* [1]	CVPR-12	2.2286	28.8833
Peng *et al.* [36]	ICIP-15	1.2209	24.4583
Galdran *et al.* [16]	JVCIR-15	2.6015	23.6818
Drew *et al.* [9]	JCGA-16	2.3856	26.5605
FU *et al.* [14]	ISPCS-17	2.8144	25.0951
Ancuti *et al.* [2]	TIP-17	3.4454	22.6962
Peng *et al.* [35]	TIP-17	2.5579	26.8123
Peng *et al.* [34]	TIP-18	1.2150	24.0727
Li *et al.* [25]	TIP-19	2.5401	28.0761
Proposed Method		**4.2262**	**20.6937**

TABLE III
Performance Evaluation of the Proposed and Existing Methods on Set of Synthetic Underwater Images

Methods	SSIM	PSNR	CIDE2000
Ancuti *et al.* [1]	0.4374	13.1104	22.8852
Peng *et al.* [36]	0.4813	14.1238	22.3985
Galdran *et al.* [16]	0.4124	13.1496	24.1212
Drew *et al.* [9]	0.4199	15.2401	19.9869
FU *et al.* [14]	0.4118	12.6402	22.5667
Peng *et al.* [35]	0.4147	14.2399	22.0700
Peng *et al.* [34]	0.3058	15.0811	22.7495
Li *et al.* [25]	0.4560	15.5333	19.3526
Proposed Method	**0.8611**	**27.8473**	**5.0763**

V. Conclusion

In this work, we have proposed an end-to-end generalized deep network to enhance the underwater images of different water type. Channel-wise feature extraction module and dense-residual network are proposed to extract the robust color features and to reduce the effect of underwater haze as well as image blurriness respectively. A synthetic underwater image database is created and used to train the proposed network for underwater image enhancement. A custom loss function is proposed to generate true edges and to preserve structural consistency. The proposed network is validated with the help of both qualitative and quantitative analysis on the real-world as well as synthetic underwater images. Extensive analysis shows that the proposed approach is superior than the existing methods for underwater image restoration.

REFERENCES

[1] C. Ancuti, C. O. Ancuti, T. Haber, and P. Bekaert, "Enhancing underwater images and videos by fusion," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit.*, 2012, pp. 81–88.

[2] C. O. Ancuti, C. Ancuti, C. De Vleeschouwer, and P. Bekaert, "Color balance and fusion for underwater image enhancement," *IEEE Trans. Image Process.*, vol. 27, no. 1, pp. 379–393, Jan. 2017.

[3] C. O. Ancuti, C. Ancuti, C. De Vleeschouwer, and M. Sbetr, "Color channel transfer for image dehazing," *IEEE Signal Process. Lett.*, vol. 26, no. 9, pp. 1413–1417, Sep. 2019.

[4] S. Anwar, C. Li, and F. Porikli, "Deep underwater image enhancement," 2018, *arXiv:1807.03528*.

[5] D. Berman, T. Treibitz, and S. Avidan, "Diving into haze-lines: Color restoration of underwater images," in *Proc. Brit. Mach. Vision Conf.*, 2017, pp. 1–12.

[6] N. Carlevaris-Bianco, A. Mohan, and R. M. Eustice, "Initial results in underwater single image dehazing," in *Proc. MTS/IEEE OCEANS Conf.*, 2010, pp. 1–8.

[7] X. Chen, J. Yu, S. Kong, Z. Wu, X. Fang, and L. Wen, "Towards real-time advancement of underwater visual quality with gan," *IEEE Trans. Ind. Electron.*, vol. 66, no. 12, pp. 9350–9359, Dec. 2019.

[8] J. Y. Chiang and Y.-C. Chen, "Underwater image enhancement by wavelength compensation and dehazing," *IEEE Trans. Image Process.*, vol. 21, no. 4, pp. 1756–1769, Apr. 2011.

[9] P. L. Drews, E. R. Nascimento, S. S. Botelho, and M. F. M. Campos, "Underwater depth estimation and image restoration based on single images," *IEEE Comput. Graph. Appl.*, vol. 36, no. 2, pp. 24–35, Mar./Apr. 2016.

[10] A. Duarte, F. Codevilla, J. D. O. Gaya, and S. S. Botelho, "A dataset to evaluate underwater image restoration methods," in *Proc. OCEANS Conf.*, 2016, pp. 1–6.

[11] A. Dudhane and S. Murala, "C^2 MSNet: A novel approach for single image haze removal," in *Proc. IEEE Winter Conf. Appl. Comput. Vision*, 2018, pp. 1397–1404.

[12] A. Dudhane and S. Murala, "RYF-Net: Deep fusion network for single image haze removal," *IEEE Trans. Image Process.*, vol. 29, pp. 628–640, 2020.

[13] A. Dudhane, H. Singh Aulakh, and S. Murala, "RI-GAN: An end-to-end network for single image haze removal," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit. Workshops*, 2019, pp. 2014–2023.

[14] X. Fu, Z. Fan, M. Ling, Y. Huang, and X. Ding, "Two-step approach for single underwater image enhancement," in *Proc. Int. Symp. Intell. Signal Process. Commun. Syst.*, 2017, pp. 789–794.

[15] X. Fu, P. Zhuang, Y. Huang, Y. Liao, X.-P. Zhang, and X. Ding, "A retinex-based enhancing approach for single underwater image," in *Proc. IEEE Int. Conf. Image Process.*, 2014, pp. 4572–4576.

[16] A. Galdran, D. Pardo, A. Picón, and A. Alvarez-Gila, "Automatic red-channel underwater image restoration," *J. Visual Commun. Image Representation*, vol. 26, pp. 132–145, 2015.

[17] K. He, J. Sun, and X. Tang, "Guided image filtering," in *Proc. Eur. Conf. Comput. Vision*, 2010, pp. 1–14.

[18] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2341–2353, Dec. 2011.

[19] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit.*, 2016, pp. 770–778.

[20] A. G. Howard *et al.*, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," 2017, *arXiv:1704.04861*.

[21] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit.*, 2017, pp. 4700–4708.

[22] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit.*, 2017, pp. 5967–5976.

[23] M. Jian, Q. Qi, J. Dong, Y. Yin, W. Zhang, and K.-M. Lam, "The ouc-vision large-scale underwater image database," in *Proc. IEEE Int. Conf. Multimedia Expo*, 2017, pp. 1297–1302.

[24] I. Kavasidis, S. Palazzo, R. Di Salvo, D. Giordano, and C. Spampinato, "An innovative web-based collaborative platform for video annotation," *Multimedia Tools Appl.*, vol. 70, no. 1, pp. 413–432, 2014.

[25] C. Li *et al.*, "An underwater image enhancement benchmark dataset and beyond," *IEEE Trans. Image Process*, vol. 29, pp. 4376–4389, 2020.

[26] C. Li, J. Guo, and C. Guo, "Emerging from water: Underwater image color correction based on weakly supervised color transfer," *IEEE Signal Process. Lett.*, vol. 25, no. 3, pp. 323–327, Mar. 2018.

[27] 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 Robot. Autom. Lett.*, vol. 3, no. 1, pp. 387–394, Jan. 2017.

[28] L. Li, J. Pan, W.-S. Lai, C. Gao, N. Sang, and M.-H. Yang, "Learning a discriminative prior for blind image deblurring," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit.*, 2018, pp. 6616–6625.

[29] A. Mittal, A. K. Moorthy, and A. C. Bovik, "No-reference image quality assessment in the spatial domain," *IEEE Trans. Image Process.*, vol. 21, no. 12, pp. 4695–4708, Dec. 2012.

[30] S. G. Narasimhan and S. K. Nayar, "Contrast restoration of weather degraded images," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 6, pp. 713–724, Jun. 2003.

[31] K. Panetta, C. Gao, and S. Agaian, "Human-visual-system-inspired underwater image quality measures," *IEEE J. Ocean. Eng.*, vol. 41, no. 3, pp. 541–551, Jul. 2015.

[32] P. Patil and S. Murala, "FgGAN: A cascaded unpaired learning for background estimation and foreground segmentation," in *Proc. IEEE Winter Conf. Appl. Comput. Vision*, 2019, pp. 1770–1778.

[33] P. W. Patil, O. Thawakar, A. Dudhane, and S. Murala, "Motion saliency based generative adversarial network for underwater moving object segmentation," in *Proc. IEEE Int, Conf. Image Process.*, 2019, pp. 1565–1569.

[34] Y.-T. Peng, K. Cao, and P. C. Cosman, "Generalization of the dark channel prior for single image restoration," *IEEE Trans. Image Process.*, vol. 27, no. 6, pp. 2856–2868, Jun. 2018.

[35] Y.-T. Peng and P. C. Cosman, "Underwater image restoration based on image blurriness and light absorption," *IEEE Trans. Image Process.*, vol. 26, no. 4, pp. 1579–1594, Apr. 2017.

[36] Y.-T. Peng, X. Zhao, and P. C. Cosman, "Single underwater image enhancement using depth estimation based on blurriness," in *Proc. IEEE Int. Conf. Image Process.*, 2015, pp. 4952–4956.

[37] Y. Y. Schechner and N. Karpel, "Recovery of underwater visibility and structure by polarization analysis," *IEEE J. Ocean. Eng.*, vol. 30, no. 3, pp. 570–587, Jul. 2005.

[38] N. Silberman, D. Hoiem, P. Kohli, and R. Fergus, "Indoor segmentation and support inference from RGBD images," in *Proc. Eur. Conf. Comput. Vision*, 2012, pp. 746–760.

[39] S. Zhang, T. Wang, J. Dong, and H. Yu, "Underwater image enhancement via extended multi-scale retinex," *Neurocomputing*, vol. 245, pp. 1–9, 2017.

[40] Y. Zhou, Q. Wu, K. Yan, L. Feng, and W. Xiang, "Underwater image restoration using color-line model," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 29, no. 3, pp. 907–911, Mar. 2018.