AquaGAN: Restoration of Underwater Images

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Abstract

In this paper, we propose a generative model to restore degraded underwater images considering attenuation coefficients as clue and name it as AquaGAN. Computing the attenuation coefficients as given in revised image formation model demands in-situ measurements. However, in-situ measurements in underwater scenario is infeasible. Towards this, we propose to estimate the attenuation coefficients using learning based methods and use these parameters as clue for restoration of degraded underwater images. Restoration of true colors in underwater scenario is challenging as intensity of light changes with distance. Preserving true colors during restoration by minimizing single objective function may affect the quality of restored image. Towards this, we propose to combine different objective functions for restoration of true colors. We demonstrate the results of restoration on benchmark dataset and compare the results of proposed methodology with state-of-the-art methods both qualitatively and quantitatively.

1. Introduction

In this paper, we present a novel method for estimating attenuation coefficients considering revised image formation model [1] and use the same as clue to train generative networks, towards restoration of degraded underwater images. Images captured in mist, fog, smog, smoke and water are likely to undergo degradations as light reaching the camera passing through these mediums is absorbed and scattered. The process of restoration in underwater scenario is more sensitive to absorption and scattering parameters.

Underwater domain, has not benefited from the full power of computer vision and machine learning methods as water masks many computationally valuable features of a scene [1]. An underwater photo is the equivalent of one taken in air, covered with thick, colored fog, where white point and intensity changes as a function of distance. Training learning-based methods for different optical conditions representing the global ocean, is challenging as calibrated underwater datasets are expensive and logistically difficult to capture.

Capturing underwater scene, reckons heavily on autonomous underwater vehicles (AUV) or remotely operated vehicle (ROV). AUV/ROV's are equipped with high end imaging sensors to perform underwater survey missions, such as detecting and mapping submerged archeological sites, ship wrecks [13] and rocks. Recently, there has been considerable advancements in underwater capturing equipments and technologies. However, the underwater environment still presents unique challenges unlike the above water environment [6].

Images captured underwater typically undergo degradations like direct scattering and back scattering. Direct scattering effect introduces blur there by smoothing the color transition between the pixels of an image. Back scattering introduces color cast and haze reducing the color information and masking the important features of an image. The aim of underwater restoration algorithms [6] is to recover the lost colors of an image by reducing blur and haze. Towards this, most authors in literature propose color correction [11, 28], blur and haze [17] removal architectures [32] [22] for improving the overall appearance of the image. Authors in [12] represent mathematical model [5] for degradation process of underwater images shown in Equation 1 and Equation 2. Authors in [24] [3] [16] considers attenuation coefficient β_λ to be spectrally uniform for backscattering and direct attenuation across R, G, B channels.

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

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

$$t(x,y) = e^{-\beta_\lambda d(x,y)} \tag{2}$$

where $d(x,y)$ represents horizontal depth from camera to scene.

The image formation process as given in Equation 1, constitutes true scene blended with veiling light A and

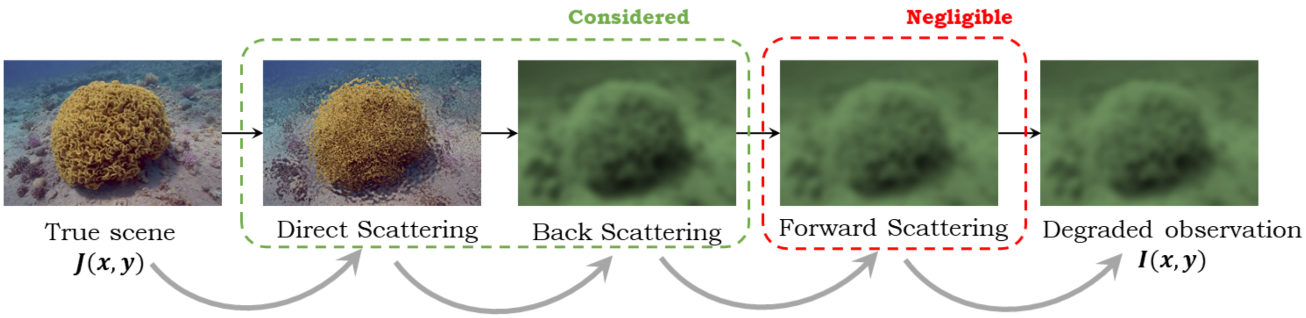

Figure 1. Degradation process during underwater image capture

transmission map $t(x, y)$ computed using scene depth $d(x, y)$ of the camera resulting into degraded image $I(x, y)$. Transmission map here describes the portion of the scene radiance, that is not scattered or absorbed and reaches the camera directly. Recovering true scene from the degraded observations needs reversing the image formation process. Combination of noise, blur, color cast make image restoration an ill posed problem. To make it a well posed, it is necessary to make certain assumption of the scene as a priori information, and use the same in restoration framework. These initial assumptions along with assumption on β_λ in traditional restoration methods limit the success of restoration framework.

Authors in [8] choose brightest pixel to predict the atmospheric light. Authors in [25] choose brightest pixel and Fattal [7] used the same as an initial conjecture. Typically, the brightest pixel might not contribute towards prediction of atmospheric light, as the brightest pixel may also belong to object of interest. To address this, authors in [9] choose brightest pixel in the local patches, considering intensities close to zero in dark channel and predicting atmospheric light from haze opaque regions of dark channel. Above methods assumed scattering coefficients to be uniform across all the channels, wavelength and depth. Considering, same coefficient for all color channels, wavelengths and depths in underwater scenes is a very crude approximation [1], however using a coefficient per channel can yield decent results. Most of the existing methods [33] [35] [30], attempt to reverse the degradation process by making some prior assumptions to recover the true scene. However, these methods are unstable, too sensitive to specific type of data [10] and work only for shorter depths. These methods consider traditional image formation model for restoration of degraded underwater images.

To overcome the limitations of traditional restoration methods, authors in [1] propose a revised image formation considering β_λ to be spectrally independent across R, G, B channels and represent the same as shown in Equation 3.

$$I(x, y) = J(x, y)e^{-\beta_c^D(v_D)d(x,y)} + A_c^\infty(1 - e^{\beta_c^B(v_B)d(x,y)}) \tag{3}$$

here $v_D = \{d(x, y),\ \rho,\ E,\ S_c,\ \beta\}$ and $v_B = \{E,\ S_c,\ \beta,\ b\}$. Let $d(x, y)$ be the horizontal depth between camera and scene, $J(x, y)$ is the true scene and $I(x, y)$ is degraded observation. ρ be the reflectance of every object in the scene, S_c be the camera spectral response, E be the scene spectral irradiance o, b be the scattering coefficient and β be the beam attenuation coefficient.

Authors in [1] use in-situ measurements for restoring the degraded observations. However, in-situ measurements are practically infeasible for real time applications. Towards this, we consider the revised image formation model for generating degraded observations (synthetic data). Unlike, the authors in [3] [16] we consider degraded observations (synthetic data) and the corresponding parameters (attenuation coefficients) as clue for the restoration.

Towards this, we model a framework for generation of synthetic data [5] [4] using revised image formation model as shown in Figure 2 and as discussed by authors in [6]. We develop an algorithm, taking true scene radiance $J(x, y)$ and its corresponding depth $d(x, y)$ as input, along with the estimated wide band attenuation coefficients. Unlike, the traditional image formation we estimate A_c^∞ as given as given by authors in [1] for R,G,B color channels. We consider 10 classes of Jerlov water types and generate 800 images for each class across 20 vertical depths. We render 1,60,000 underwater images coupled with corresponding attenuation coefficients are rendered towards training restoration framework.

Alternatively, researchers propose learning based methods for restoration of underwater images. Deep learning based solutions provide a mechanism to handle the complex non linear equations, and provide promising solutions in restoration of underwater images. Most authors in literature address the restoration process in two ways namely parametric and non parametric based. Parametric methods involves estimation of attenuation coefficients in a super-

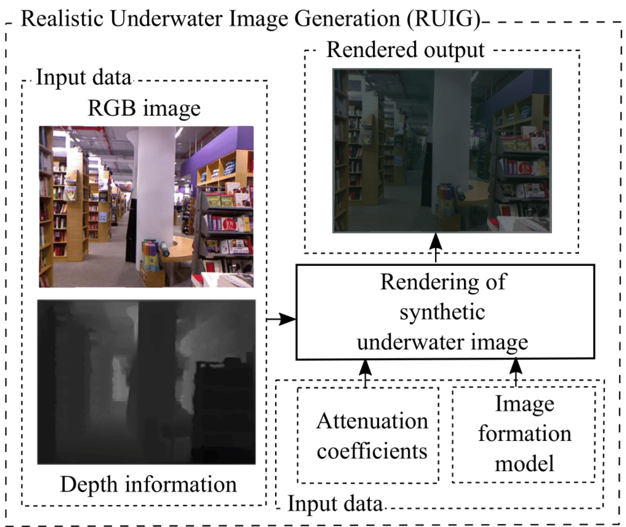

Figure 2. Framework for rendering synthetic underwater images.

vised manner and using the same in revised image formation model. Authors in [19] use generative models for image restoration in low light conditions considering content and style loss. Through literature we infer considering style loss alone results in loss of content and vice-versa. Towards this, we propose a weighted combination of content and style loss to preserve the true colors during restoration. Non-parametric based methods include learning mapping between ground-truth and degraded images ignoring the underlying dependencies of underwater environmental conditions.

The authors in [29] estimate water-light from the background region of an image assuming the variation to be minimal in such regions. Towards this, they divide the image into $8*8$ patches, and determine the patch having low variance and estimate the water light accordingly. The authors, estimate transmission map by plotting attenuation curves on R, G, B space with KD tree clustering on logarithmic values of R, G, B. The authors in [26] propose GAN architecture for synthetic data generation and propose to use U-Net for color correction and dehazing. The authors in [2] consider multi-spectral profiles of different water types to estimate attenuation ratios of blue-green, blue-red channel and perform dehazing and color correction. Most of the authors in literature perform non parametric based restoration ignoring the underlying dependencies of water type and depth.

The authors in [20] estimate priors (atmospheric light and transmission map) iteratively. The authors make initial assumptions about the prior and iteratively refine them through gradient based optimization. For each iteration, the reconstructed image is compared against the ground-truth. The authors in [14] propose recurrent neural networks with iterative framework to de-haze an image. The authors in [34] propose to dehaze an image with three steps. In first step, the transmission map is estimated from the input hazy image and in second step it is concatenated with high dimensional feature map using GAN framework. Finally, the concatenated maps are fed into the guided dehazing module to estimate the dehazed image by minimizing the combination of perceptual loss and Euclidean loss. All the methods discussed, try to recover true scene from degraded observation for on air images using atmospheric dehazing models. However, the novelty lies in developing an end to end learning based framework towards estimating attenuation coefficients in underwater environment.

Towards this, we intend to perform parametric restoration considering attenuation coefficients as clue in restoration process, in particular

- We propose AquaGAN towards restoration of degraded underwater images with attenuation coefficients as clue.
- We propose to estimate the attenuation coefficient A_c^∞ with learning based techniques, and use the same as a clue towards restoration.
- We propose a composite loss function (weighted combination of content and style loss) for restoration of degraded underwater images.
- We demonstrate the results of restoration (AquaGAN) using synthetic and benchmark real datasets, and compare the quality of restoration with state-of-the-art techniques using qualitative and quantitative metrics.

In Section 2, we discuss the proposed methodology for estimation of attenuation coefficients. In Section 3 we discuss the proposed generative model (AquaGAN) for restoration of underwater images. We discuss the results of the proposed methodology in Section 4 and compare the same with state-of-the-art techniques. We present conclusion remarks in Section 5.

2. Estimation of attenuation coefficient (A_c^∞) veiling light

We model estimation of attenuation coefficients considering the Equation 4 and Equation 5 as given by authors in [1]. During synthetic data generation, authors in [6] estimate A_c^∞ and introduce the effect of the same for on air images towards generating degraded underwater observations. The synthetic data coupled with ground truth parameters is used to train deep learning algorithms for facilitating restoration of degraded images captured underwater.

The atmospheric light (A_c^∞) light also known as ambient light is scattered along the line of sight. Typically ambient light gets attenuated with vertical depth before reaching

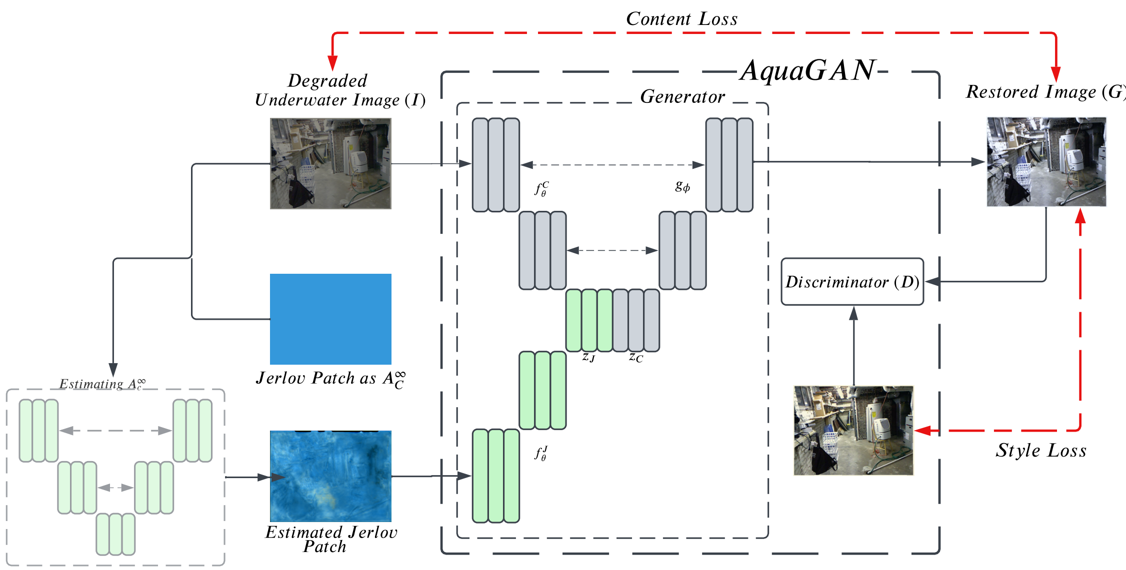

Figure 3. Proposed framework of AquaGAN for restoration of degraded underwater images.

the actual scene and often fails to reach beyond $20m$ - $30m$ depth and we assume, the effect introduced by scattering of light in an image is fairly uniform. Capturing underwater scene at depth of $20m$ and above demands artificial source of light, to mimic the behaviour of natural light and the ocean divers use head mounted artificial source of light. However, the head mounted artificial light is unstable due to water currents leading to absorption and scattering.

Restoration of lost information due to scattering and absorption of artificial source of light is the key towards success of underwater imaging. From the literature we infer, the atmospheric light is present in the background of an image leading to formation of tint in underwater scenario. Typically, UNet [23] algorithm is used for foreground-background segmentation. Towards this, we use UNet [23] auto encoder as shown in Figure 3 to estimate atmospheric light. We use the synthetic data coupled with ground-truth information to train the UNet auto encoder. We test the performance of the model on UIEBD [15] benchmark dataset and use this information as clue to train the proposed AqGAN. We demonstrate the performance of the model qualitatively in Figure 4.

$$\mathbb{A}_c^\infty = \int_{\lambda_1}^{\lambda_2} S_c(\lambda) A^\infty(\lambda) d\lambda \tag{4}$$

$$A^\infty(\lambda) = \frac{b(\lambda)E(d,\lambda)}{\beta(\lambda)} \tag{5}$$

3. AquaGAN: Proposed framework for Restoration of Underwater Images

We propose Aqua Generative Adversarial Network (AquaGAN), to learn mapping between ground-truth image and the generated image. Unlike typical GAN, we include 2 encoders a decoder and discriminator for restoration of degraded underwater images. Second encoder facilitates learning of additional information about scattering and absorption towards improved restoration. In proposed model, we use UNet [23] encoder- decoder architecture along with discriminator. Degraded underwater image (I) is input to first encoder f_θ^c. The latent representation of I, z_c is of dimension $N*1$. Estimated Jerlov patch is input to second encoder f_θ^J to generate the latent space z_j of $N*1$ dimension. We concatenate and find the correlation of the encodings z_j and z_c and create a single $(2N*1)$ vector representation. The decoder g_ϕ takes in $(2N*1)$ dimension vector representation of latent space to restore the image. We include discriminator (D) as additional module to penalize the generator for producing convincing results. The novelty of this work lies in considering the attenuation coefficients as additional clue towards restoration. We propose content loss between degraded underwater image I and decoder generated image G. We include style loss between generated image G and the corresponding ground-truth information GT.

3.1. Loss Function

In this work, we propose a composite loss function (weighted combination of content and style loss) for restoration of degraded underwater images. Content loss

Figure 4. Estimation of atmospheric light with the proposed framework. First row corresponds to input images. Second row shows the estimation of atmospheric light using the proposed framework. The whitish region within the image indicates the degraded area due to scattering of atmospheric light.

Figure 5. Restored synthetic underwater images with proposed framework. First column, shows ground-truth images, Second column shows rendered synthetic underwater images considering synthetic underwater generation method proposed in [6] at $5m$ depth, Third column shows the restoration results on synthetic data with our proposed framework. Fourth column shown rendered synthetic underwater images considering synthetic underwater generation method proposed in [6] at $9m$ depth. Fifth column shows the restoration results on synthetic data with our proposed framework.

makes the generated image and the content image close in content features and helps preserving the true features of an image. Content loss takes in two arguments, the input image I, generated image G and is represented in Equation 6.

$$C_L(I,G) = \frac{1}{2}\sum_{i,j}((f_\theta^c((I)_{i,j})) - (g_\phi((G)_{i,j})))^2 \quad (6)$$

Here i, j indicate i^{th} filter at position j in layer l. We compute gram matrix style loss between generated image (G) and corresponding ground- truth image (GT). The style of the ground-truth (GT) image is enforced on generated image (G) to facilitate improved restoration. The gram matrix style loss is shown in Equation 7.

$$S_L(GT,G) = \frac{1}{4N^2M^2}\sum_{ij}(g_\phi((G)_{ij}) - (GT)_{ij})^2 \quad (7)$$

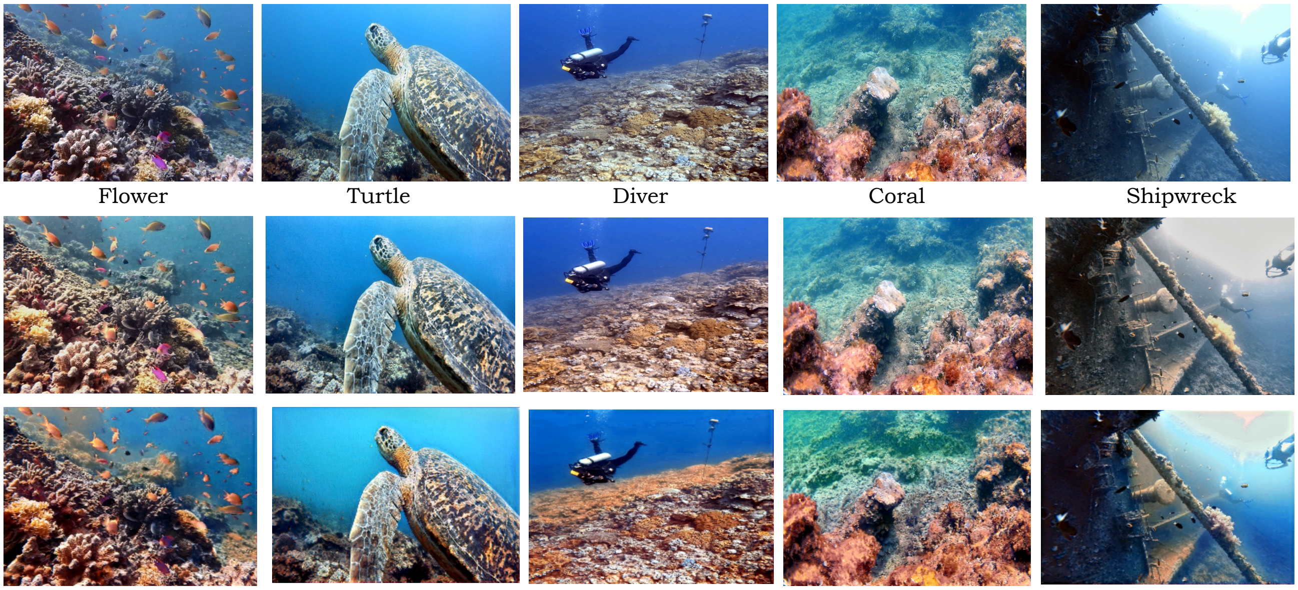

Figure 6. Restoration of real (UIEBD dataset) underwater images. First row shows the input images, Second row corresponds to restoration results of authors in [15], Third row shows restoration results of proposed framework.

We propose to consider weighted combination of content and style loss towards restoration of underwater images as shown in Equation 8.

$$Total_loss = \beta(C_L(I,G)) + \alpha(S_L(GT,G)) \quad (8)$$

We carry out experiments with different α and β values and observe for $\alpha = 0.7$ and $\beta = 0.3$ quality of restoration is better. The results and the corresponding quantitative scores are shown in Table 1 and Figure 8.

We use total of 25000 generated synthetic images and combine with UIEBD dataset [15] for training the architecture. We divide the dataset in the ratio 80:10:10 for training, validation and testing. We train the architecture for 1200 epochs using learning rate $lr = 0.0001$ with adam optimizer. We demonstrate the results of restoration on synthetic and UIEBD dataset and compare the same with state-of-the-art methods in Section 4.

4. Results and Discussions

In this section, we demonstrate the results of proposed framework qualitatively and quantitatively. We demonstrate the restoration results on synthetic data and real underwater images using UIEBD dataset as shown in Figure 5 and Figure 6 respectively. As intensity of light varies with respect to depth, restoring true colors considering horizontal depth is challenging in underwater scenario. Unlike the authors in [6], we claim restoration results of our methodology performs better with respect to infinite depth between camera and the scene. We compare the results of proposed framework with no reference quantitative metrics as shown in Table 2.

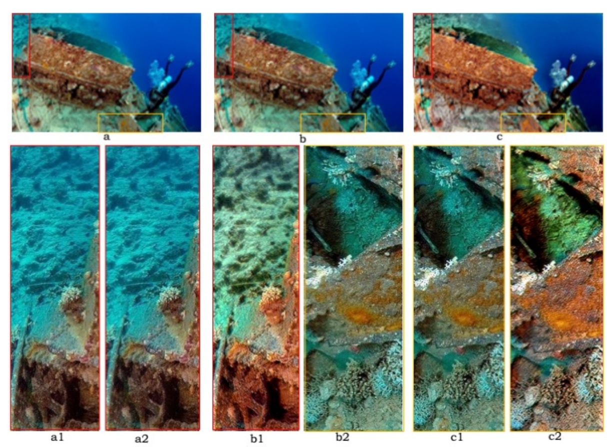

Figure 7. Restored underwater images with proposed methodology. a) Corresponds to input image. b) Shows the restoration results of authors in [15]. c) Depicts the restoration results of proposed methodology. a1 and a2 corresponds to highlighted region within the image a, b1 and b2 shows the corresponding restoration results of highlighted region within image b by authors in [15], c1 and c2 shows the corresponding restoration results of highlighted region within an image with the proposed framework.

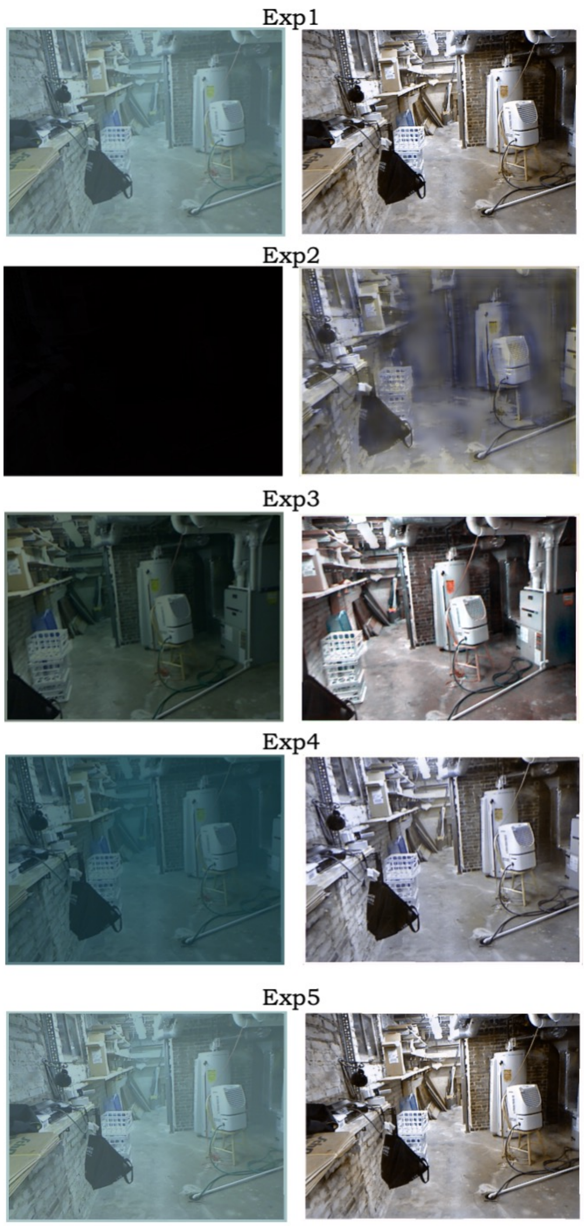

Figure 8. Experimental results with different loss functions on synthetic data and the corresponding quantitative metrics are shown in Table 1. We observe the propose combinational loss function ($\alpha = 0.7$, $\beta = 0.3$) is better in comparison with other loss functions.

5. Conclusions

In this work, we have proposed a novel method for restoration of degraded underwater image with attenuation coefficients as clue. We have discussed on training generative network AquaGAN using synthetic underwater images. We have proposed a weighted combination of content and style loss first time ever for restoration of degraded under-

Table 1. Quantitative scores for the results shown in Figure 8. We carry out experiments with different loss functions and show proposed combinational loss function ($\alpha = 0.7, \beta = 0.3$) is better in comparison with other loss functions.

Details	Loss Functions	PSNR	SSIM
Exp1	SSIM+ MSE ($\alpha = 0.6, \beta = 0.4$)	14.99204	0.38658
Exp2	SSIM+MSE ($\alpha = 0.3, \beta = 0.7$)	11.61024	0.26363
Exp3	StyleLoss + SSIM ($\alpha = 0.3, \beta = 0.7$)	9.26086	0.18410
Exp4	StyleLoss+ContentLoss ($\alpha = 0.5, \beta = 0.5$)	11.54101	0.23082
Exp5	**StyleLoss+ContentLoss+ BCELoss(Discriminator)** ($\alpha = 0.7$**,** $\beta = 0.3$)	**26.18025**	**0.96291**

water images. We show restoration is sensitive to the attenuation coefficients and claim to improve restoration considering it as clue. We have demonstrated the results of proposed framework trained using synthetic underwater images on benchmark dataset. We have compared the performance of proposed methodology with state-of-the art methods using appropriate quantitative metrics.

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Table 3. Quantitative metrics for restored synthetic underwater images as shown in Figure 5.

#	Dataset	PSNR	SSIM
1	Synthetic_1	17.42476	0.85209
2	Synthetic_2	19.01572	0.88026
3	Synthetic_3	26.37266	0.88557
4	Synthetic_4	21.48329	0.76341
5	Synthetic_5	17.4247	0.85209
6	Synthetic_6	19.01572	0.88026

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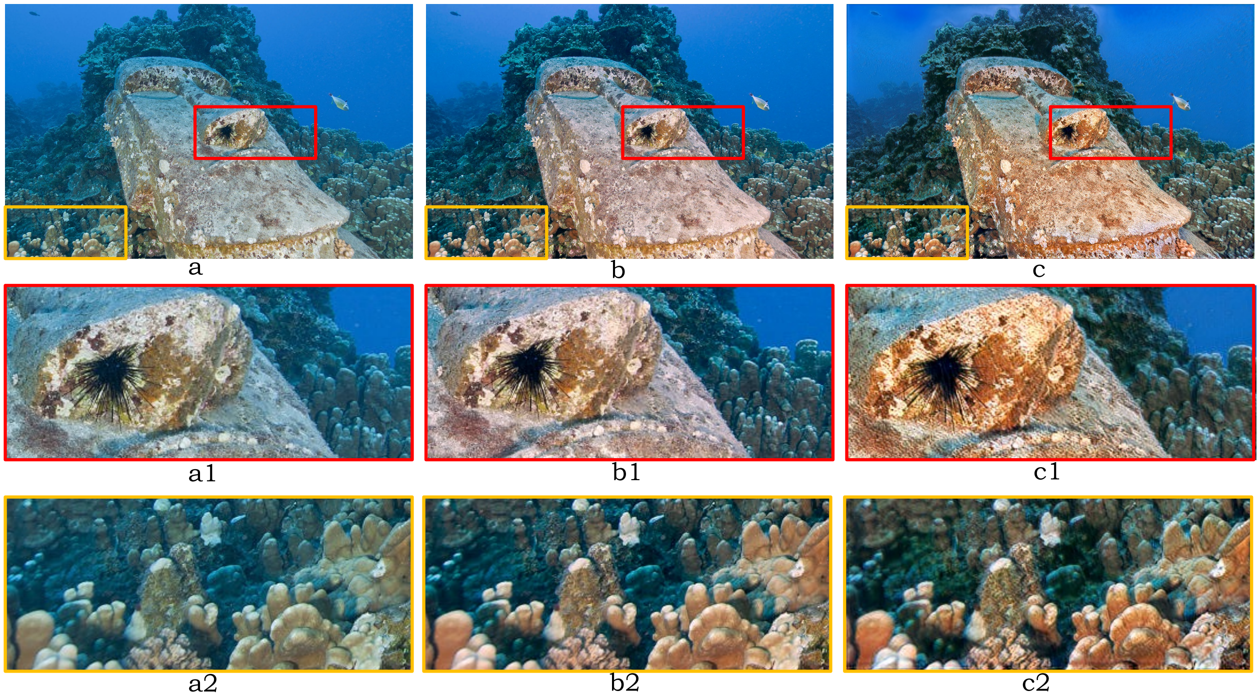

Figure 9. Restored underwater images with proposed methodology. a) Shows input image, b) Depicts restoration results of authors in [15], c) Shows the restoration results of proposed methodology. a1 and a2 corresponds to highlighted region within the image a, b1 and b2 shows corresponding restoration results of highlighted region within image b by authors in [15], c1 and c2 shows the corresponding restoration results of highlighted region within an image with the proposed framework.

Table 2. Quantitative metrics (UCIQE [31], UIQM [21], CCF [27]) of our method with the authors in [15]; Table depicts the quantitative scores computed using the platform PUIQE [18] for the images depicted in Figure 6. (↑) indicates higher score is better.

#	Dataset	UCIQE (↑)		UIQM (↑)		CCF (↑)	
		UIEBD	Ours	UIEBD	Ours	UIEBD	Ours
1	Flower (846)	0.65613	**0.67971**	0.77535	**0.83305**	29.50441	**36.23986**
2	Turtle (833)	0.65350	**0.69247**	0.77636	**0.84087**	24.16958	**28.33603**
3	Diver (799)	0.67568	**0.69994**	0.88286	**0.93680**	26.67109	**61.35818**
4	Coral (815)	0.66311	**0.67053**	0.85674	**0.88354**	27.61010	**34.89841**
5	Shipwreck (798)	0.57470	**0.63030**	0.56608	**0.60003**	18.07370	**22.51157**

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