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Research Article

NNUIE-GAN: Near Natural Underwater Image Enhancement Based on Generative Adversarial Network

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ABSTRACT

Underwater images are often prone to many non-linear distortions due to different underwater light interaction phenomenon. This contributes to colour distortion and low contrast which severely affects visual perception of that scene. Now, in today's world many underwater expeditions rely on visual perception of underwater world, which makes underwater image enhancement techniques very important. In the present work, Generative Adversarial Network based model NNUIE-GAN is introduced for real time underwater image enhancement. In this work, generator is a U Net based architecture which is tuned to process fewer parameters and generate more natural looking images by enhancing the underwater image quality. In order to consider image features at both local level and global level perspective, dual discriminator is realized wherein patch level information is processed. To bring in this effect, perceptual quality of the image in terms of local texture, global content and illumination smoothness is considered for construction of loss function. The effectiveness of the loss function is tested on the ground of qualitative and quantitative analysis. The results validated the capability of NNUIE-GAN to improve visual perception of underwater images by enhancing primary characteristics such as colour correction and image clarity improvement. Thus, appropriate tailoring of the loss function can alleviate the visual perception of image in real time processing.

Keywords: Underwater image enhancement; natural image quality; generative adversarial network.

INTRODUCTION

Under water images require immense processing to reveal its true nature, after which it can be useful to extract meaningful information. Now a days, autonomous under water vehicles (AUVs) and unmanned underwater vehicles (UUVs) mostly rely on under water images processing quality and speed. These AUVs and UUVs are used for marine resource exploration [1]. These vehicles are also used for deep-water net fishery farming and artificial fishing reef expeditions. Along with this many other applications such as underwater archaeology, underwater shipwreck observatory and offshore petroleum engineering are also keen in using these AUVs and UUVs. All these activities wherein aquatic resource development and conservation activities are carried out became progressively important globally and the focal point of international strategic development significant worldwide and are involved in development of international strategies.

Knowing the strategic importance of these applications, it is confirmed that underwater imaging ability holds significant value and is in demand to cater many sectors. However, the ground truth about underwater imaging is, as compared to images from the terrestrial environment, underwater imaging suffers from severe underexposure and other underwater light interactions phenomena due to which color distorted, blur and therefore severely degraded poor underwater images are captured [2, 3]

Owing to these, lot of researchers actively participated in finding solutions for underwater image refining and enhancing. It is observed that, non-linear image distortions of underwater images is due to different light attenuation properties of the water. More often, red colour gets absorbed till it reaches deep down in waterbodies which causes green or blue hue [4], leading to blurred, low-contrast, and often color-degraded images. Some physics-based models are designed considering these aspects for dehazing and color correction [5, 6]. However, many times these models rely on depth of scene and optical quality of water which may not be available readily, this may cause serious concern about the image enhancing capability. Similarly, these methods are usually computationally expensive which is another major concern.

In this scenario, learning-based methods can be tuned to provide more viable solutions. Several such models producing state-of-the art performance are tailored to provide best fit technical assistance for underwater image enhancements (UIE). In this niche, convolutional neural networks (CNNs) are designed and trained on large datasets, which tends to provide reliable performance [7]. To address the color deviation and blurriness, Wang et al. [8] proposed two sub networks based framework, which is tuned for defogging and corrections. Similarly, in order to suppress image noise and enhance image contrast, a CNN based framework is trained using a set of image quality indicators, which improves the UIE performance [9]. It is observed that CNN-based frameworks with powerful learning abilities produce better UIE performance as compared to the models extensively trained on specific datasets. However, if the test and the train sets are significantly different, the performance of CNN-based models show poor performance, which may be due to constraints posed by physical models [10].

On the other hand, generative adversarial network (GAN) [11] is first employed for image style transfer task and then progressively applied for other vision correction fields. Alongside, use of GAN based framework is proposed by Li et al. [12] for UIW and referred as WaterGAN, which is used for transferring style of normal image to underwater image. Likewise, many researchers started building GAN-based frameworks for UIE to offer better possible UIE strategies. Different perspectives of tailoring generators are used to minimize generator loss and simultaneously various loss functions are fused together to minimize discriminator loss. Despite of many strategies in case of UIE strategies, still, there exists room for further improvement in feature utilization [13].

In the view of this expedition in UIE field, the present study focuses on tailoring the GAN based framework, wherein generator and discrimination both are tailored to improve UIE performance. To minimize the low contrast issue of the generated image, NIQE is considered in designing loss function of generator. Moreover, owing to the limitations of Patch-GAN in guiding the generator to produce images with realistic details, herein, a dual-discriminator is designed to produce feedback at local level of the images which will help in producing natural-looking images. Thus, an image is evaluated in terms of its global content, local texture and illumination smoothness, based on which a multi-term loss function is formulated. The performance of the model is tested on publicly available datasets.

LITERATURE REVIEW

Many research groups and scholars have put together efforts to develop underwater vision technology. In general, the strategies like image enhancement-based methods, image restoration-based methods, polarization imaging-based methods and deep learning-based methods are developed for improving underwater image quality.

However, in the era of recent technological advancements, deep learning-based methods gain preference over other methods, since it allow to improve underwater image quality substantially without complex modelling. Moreover, this type of framework show high generalization capability since dependencies on parameters in traditional methods can be reduced in these models.

Some frameworks such as Shallow–UWNet [14] are designed with reduced number of model parameters but still demonstrated substantial UIE. Similarly, a group of researchers [15] demonstrated UIE by introducing normalization method for the tail of UIE methods. Whereas Fu et al. [16] considered UIE as a task wherein one input can be made correspond to multiple outputs using conditional variational autoencoder (cVAE) and further with adaptive instance normalization methods PUIE–NET is proposed which can produce UIE of high diversity content. Despite of these efforts, UIE produced using these methods show some fogginess and distorted colour effects in many samples. Besides this, these methods are poor in generalization and therefore different style images specifically with significant feature loss often produce unstable enhancement.

However, as discussed earlier, GAN based architectures provide substantial realms to tailor frameworks. Therefore, many UIE frameworks consider GAN as foundational model and try to tailor the architecture so that UIE can be achieved. In line with the previously discussed examples, the constraint generator is used to develop conditional generative adversarial network (cGAN) [17], by virtue of which pixel-to-pixel mapping from any source domain to the desired target domain can be learned and used for improving underwater image quality.

On the similar lines, CycleGAN [18] is proposed, which utilizes the cyclic consistent loss of two generators and discriminators to style transfer of air images to the underwater images. Inspired by this, a group of researchers [19] designed a framework which utilizes multinomial loss function to transfer the colours of images correctly with minimum supervised learning needed. Similarly, in case of UWGAN [20] a multi-scale feature extraction module is created to tailor GAN and achieve UIE. Despite of multiscale feature extraction module, this model produced images with distorted colour and checkerboard artifacts. Thereafter, researchers also tried to find UIE methods for real time applications. In this niche, a group of researchers introduced FUnIE–GAN [21] and achieved substantial UIE in real time scenarios. However, trade-off between real time application and enhancement ability made this to compromise on enhancement quality. This is due to the fact that real time application allowed to consider fewer parameters for UIE which ultimately restricted enhancement capability. On the similar lines, AUIE–GAN [22] is proposed for faster processing without much modelling complexity. In this model, global feature vectors and self-attention skip connection are introduced for grasping global features and modified discriminator structure is used for UIE. Some group of researchers also considered physical models along with U-Net [23] as base model and modified it for feature utilization and hence UIE [24, 25]. We propose NNUIE-GAN, which is Near Natural Underwater Image Enhancement based on Generative Adversarial Networks. We adopted FUnIE-GAN as our base model and modified generator and discriminator architecture for Near Natural Underwater Image Enhancement. In case of FUnIE-GAN, VGG-19 network is used for extracting advanced features. However, the main purpose of designing loss function is to prompt G to generate more natural looking image out of underwater image. Therefore, in this work VGG-19 network is replaced with ConvXNet [26] owing to its capability of better numeric stability for content loss. Additionally, since the visual perception of natural image shows local smoothness as its primary characteristic, we incorporated illumination smoothness loss to the objective function of NNUIE-GAN.

METHODOLOGY

Proposed Architecture for NNUIE-GAN

The architecture for fast UIE is proposed as FUnIE-GAN [21]. Considering it as base models, a modified architecture NNUIE-GAN is proposed in the present work. In this NNUIE-GAN, a multi-modal objective local texture and function is used to train the algorithm. For enhancing the image quality parameters such as local texture, style information and global similarity are considered. Let's consider, I_D be underwater or degraded image which we want to transform in to enhanced image I_E. In the present work, NNUIE-GAN is trained to learn mapping as $I_D \rightarrow I_E$. As revealed earlier, FUnIE-GAN is used as base model and discriminator is tailored to generate natural looking images at both the global semantic and local detail levels.

The FUnIE-GAN proposed an improved U-Net architecture [23] as a generator but more simpler version of it is deployed for the present work. It consists of encoder–decoder (e1 e5, d1 d5) as main components of architecture.

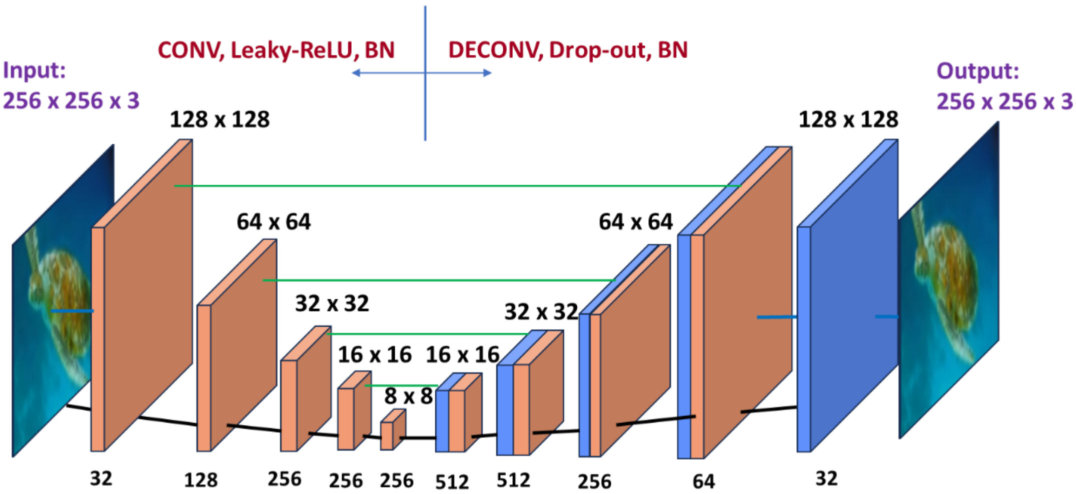

Fig. 1. Generator of NNUIE-GAN containing five encoder-decoder pairs with mirrored skip-connections.

The structural details of generator are depicted in Fig. 1. On the left most side of the image, input image is shown. It is then followed by encoder, which consists of five orange-coloured rectangular boxes representing multi-channel feature map. Images with five-layer multi-channel features are obtained after convoluting 4 × 4 convolution kernel and simultaneously performing nonlinear operations and batch normalization.

Similarly, the other half of Fig. 1. represents decoder part of generator. It consists of five multi-channel feature maps, represented by rectangles, four of which are mixed coloured (orange and blue) and one is blue. For obtaining multi-channel feature map, the operations such as deconvolution of 4 × 4 convolutional kernel, drop-out, and batch normalization are used. In this way, the deep information from the image is extracted using decoders by continuous up sampling and expanding image size.

The processing of image using generator is also depicted in Fig. 1., wherein, adjacent convolution layers are connected using horizontal lines (black lines) which show convolution or deconvolution operation taking place in between them. Whereas splicing operations are shown by the lines which are used to connect non-adjacent convolution layers (green lines). In case of mixed rectangular boxes, down-sampled multi-channel feature map are represented by orange boxes, while up-sampled multi-channel feature map are represented by blue boxes.

The left half of image shows input processing of the generator, wherein the input image is of the size 256 × 256 with three channels. It is to be noted that only 256 feature-maps are learned by encoders which are of size 8×8. Afterwards these feature maps along with input received from skip-connections are utilized for learning image feature details by decoder (d1-d5). The decoders then learn to generate an enhanced version of image with the size same as input (256 × 256 × 3). Thus, through each down sampling step of the encoder, the image feature map reduces to half, whereas, in case of decoder, each up-sampling process doubles the feature map. To achieve this, the encoder and the decoder are connected via the feature maps of the corresponding layers. The multi-channel feature maps of both encoders and decoders are correspondently related to each other as (e1,d5), (e2,d4), (e3,d2), (e4,d4). This stitching process enhances performance of generator by combining information of deep features and shallow features.

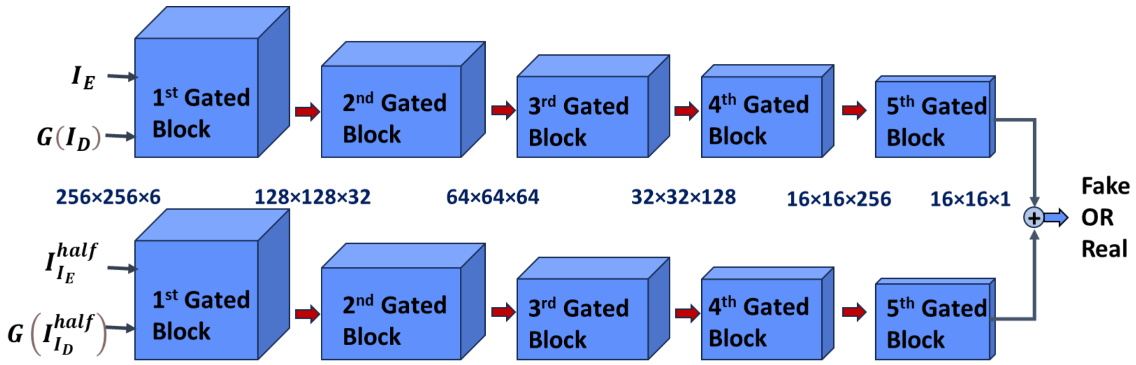

Fig.2. Dual Discriminator each with 5 gated blocks which processes patch level information of size 16 × 16.

In this work, Markovian Patch-Gan is used for discriminator network architecture [27]. It is particularly tuned to capture the information related to local texture and style of an image. This helps in prevalently identifying blue-green background in the underwater images. Moreover, it is trained to analyse small patches of image to distinguish and learn patterns. However, it does not consider global level features which are important to bring in more realistic image correction or enhancement. In order to introduce global features, Markovian Patch-Gan is modified as dual discriminator. With this modification, now generator considers not only details at local level but also the global semantic levels.

The architecture needed for this modification is depicted in Fig.2. To achieve a 16×16×1 output five Gated Blocks are utilized which are densely connected, these blocks are used to process a 256 × 256 ×6 input. However, to consider local level details along with global features, the discriminator is feed with the original image (both I_D and I_E)and with its corresponding 2× down-sampled image (both I_D^{half} and I_E^{half}) as shown in Fig.2 . To improve the discriminative ability, the gated Blocks are modified as shown in Fig.2. the flow of information is controlled using gating mechanism, which is product of two parallel paths taken as element-by-element. As as important modification, Tanh's non-linearity is used to modify one of its paths. This supresses the value flowing through the network and limits it in the range of −1and1. This refrains network from producing over exposed images.

Adversarial Loss function

The optimization method is used to train dual discriminator. Let, G be the generator and D represents discriminator. The generator tries to generate as natural looking image as possible and D tries to check for the discrepancies. As described earlier, let I_D and I_E be the distorted or underwater Image and enhanced or original natural image respectively. Similarly, both I_D^{half} and I_E^{half} be the 2× down-sampled underwater Image and enhanced image respectively. With these notations the, the optimization followed in the present work is as follows.

$$\frac{min}{G}\frac{max}{D}\ E_{I_E}\left[log\ log\ D(I_E)\right] + E_{I_D}\left[log\ log\ \left(1 - D\big(G(I_D)\big)\right)\right] \tag{1}$$

$$\frac{min}{G}\frac{max}{D} E_{I_E}^{half}\ \left[log\ log\ D(I_{I_E}^{half})\right] + E_{I_D}^{half}\left[log\ log\ \left(1 - D\left(G\big(I_{I_D}^{half}\big)\right)\right)\right] \tag{2}$$

Further this leads towards adversarial loss functions as L_{A1} and L_{A2} for Images normal size and down sampled size respectively can be stated as follows.

$$L_{A1}\ (G, D) = E\ \|\ log\ log\ \left(1 - D\big(G(I_D)\big)\right)\ \|_1 \tag{3}$$

$$L_{A2}\ \ (G, D) =\ E\ \|\ log\ log\ \left(1 - D\left(G\big(I_{I_D}^{half}\big)\right)\right)\ \|_1 \tag{4}$$

Global Similarity:

It is observed that, if loss function is added to objective function, G can learn from globally similar space [27, 28]. Therefore, difference between real natural image I_E and generated image $G(I_D)$ is calculated

$$L_G = E\ \|I_E - G(I_E)\|_1 \tag{5}$$

Image Content:

The loss term is introduced in objective function so that G can consider it as feature representation for target. This enables G to produce enhanced images with feature representation same as that of natural looking image. For this, the image content function Φ (·) extracted as high-level features using pre-trained ConvXNet network. The distance between feature representations of the real image (Grounf truth image) is measured with respect to that of feature representations of generated resultant image.

$$L_{con} = E\ \|\Phi\ (I_E) - \Phi\ G(I_D)\|_2 \tag{6}$$

Illumination Smoothness Loss:

To enhance the generalization capacity of network and to maintain monotonic connection between adjacent pixel, illumination smoothness loss is constituted in objective function.

$$L_{tvA} = \frac{1}{N}\sum_{n=1}^{N}\quad \sum_{c\in\xi}\quad \left(|\Delta_x A_n^c| + \left|\Delta_y A_n^c\right|\right)^2, \xi\ =\ \{R, G, B\} \tag{7}$$

In this equation, number of iterations are represented by N. The gradient operations are denoted as Δ_x and Δ_y, which are operated in horizontal and vertical directions respectively. Using a simple network illumination parameter map A is obtained. It is the fully convolutional network wherein each layer is of 3 × 3 convolution kernels.

Total Loss

Summing up all the loss function can be used to conclude total loss which is considered to add in objective function. Therefor, total loss (L_{Total}) is calculated as follows.

$$L_{Total} = \lambda_A(L_{A1} +\ L_{A2}) +\ \lambda_G L_G +\ \lambda_c L_{con} +\ \lambda_I L_{tvA} \tag{8}$$

The λ_A, λ_G, λ_C, λ_I are scaling factors, which act as weights for the losses. These are empirically tuned as hyper-parameters with values λ_A= 0.6, λ_G=0.5, λ_C=0.3, λ_I=20.

EXPERIMENTAL RESULTS

The Experimental Configuration

The deep learning framework PyTorch is utilized the present work. The NVIDIA RTX 3080 is used for implementation and for training 100 epochs are used. For training and evaluation of the proposed model, the subset of EUVP dataset is used in the present study [21]. This dataset is the collection of images during ocean exploration events. Images are from different environments and therefore location wise variations in visibility conditions are captured. There is default partition available in EUVP dataset as training data and evaluation data. In this study, 11,500 images are used for training and verification is carried out using 1200 images. For testing 550 images are used. Our model is trained using ADAM optimizer with setting batch size as 8 and 0.0005 as learning rate of G.

The colour and structure similarity between enhanced images using NNUIE-GAN and ground truth images are compared to quantify and evaluate the performance of the proposed NNUIE-GAN. For this, peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) which are well known standard metrics are used [29]. In general, higher the PSNR and SSIM values better is the performance considered.

In order to observe the enhancement ability of the present model, we compared performance of NNUIE-GAN with several other underwater image enhancement strategies which include CNN-based model and GAN-based model. The Table 1 summarizes PSNR and SSIM values of all the models with which NNUIE-GAN is compared. Similarly, Fig. 3. Shows, outcome compared on the basis of qualitative performance and comparison with other models.

Table 1: Quantitative comparison in terms of PSNR and SSIM of NNUIE-GAN with other models.

Models	PSNR	SSIM
Water-Net [30]	19.113	0.7971
PUIE–NET [16]	19.6275	0.9028
Semi–UIR [31]	22.305	0.9192
Shallow–UWNet [14]	26.762	0.81
CycleGAN [18]	17.14	0.64
FUnIE–GAN [21]	21.36	0.8164
LU2Net [32]	25.549	0.868
NNUIE-GAN	27.234	0.87

In earlier attempts for UIE, Water-Net [30] is proposed wherein UIE is achieved by fusing the inputs with the predicted confidence maps. The results generated were visually pleasing, the method faced difficulty in completely removing effect of backscatter especially for far distances. Despite of this, Water-Net was able to produce much better performance than existing methods of that time. The PUIE–NET shows slightly better performance, however, still shows fogging effect in the enhanced images. Similarly, Semi–UIR is also a deep learning-based method, shows impressive performance. Despite of this, some images are blurred and showed reduced visibility quality. Another model Shallow-UWnet was built to process images in real time and therefore less number of parameters are considered for modelling. This compromises the image quality and thus showed weaker UIE performance. The Semi–UIR is also a deep learning-based method and displayed very pleasant enhancement results. However, some images still show blurring effect.

In most of the GAN based UIE methods, CycleGAN is considered as benchmark performance to be compared with. Most of the time UIE method struggle to achieving color consistency or hue rectification. Even though, CycleGAN handles colour correction very comfortably and produce remarkable colour correction, it struggles in hue correction from the image which hampers the clarity of enhanced images. As compared to this, FUnIE-GAN performs better on both colour consistency and hue rectification fronts and produce comparatively better results. Also, as compared to the physics-based models wherein waterbody information and scene depth are needed in prior, the FUnIE-GAN shows much better performance [21]. However, both the methods viz., FUnIE-GAN and ShallowUWnet are tailored to improve real time UIE performance and therefore less number of parameters are used while modelling the workflow. This shows the impact on color consistency and hue rectification as compared to other recent methods.

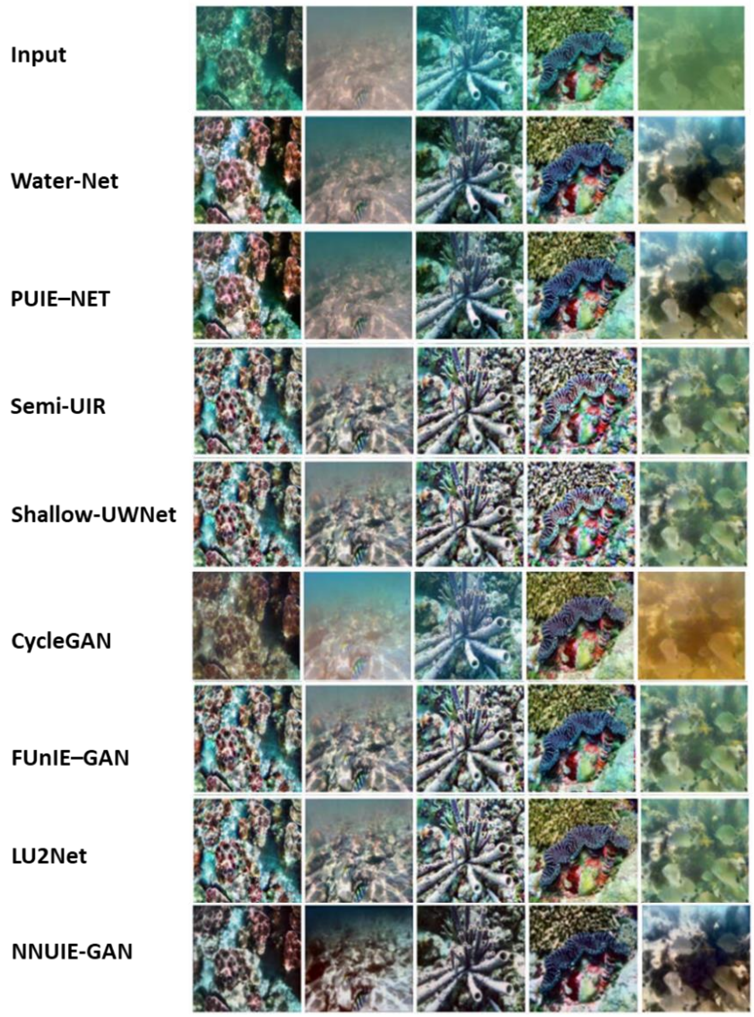

Fig.3. Comparison of qualitative performance of NNUIE-GAN with other existing models.

Also, LU2Net is proposed as Real-time UIE model which is formulated as Lightweight Network. A U shape network is tailored for real time image enhancement by incorporating axial depth wise convolution, introducing domain-specific knowledge in architecture of model and the channel attention module. This becomes less computationally expensive and parameter intense and therefore improves processing speed and provides improved UIE results. As can be seen in Table 1., the UIE achieved using NNUIE-GAN shows better performance than other models. The NNUIE-GAN shows PSNR as 27.234 and SSIM as 0.87, outperforming other methods. Also on visual aspect basis, NNUIE-GAN can recover true colour and sharpness of the objects in the image. In addition to this, it rectifies greenish hue present in underwater images and takes action to enhance the global contrast. These actions fulfil primary criterion of a model to be a good underwater image enhancer. Therefore, NNUIE-GAN is capable of producing images with richer colours, higher contrast and more details. It can be explained on the basis of better tailoring of loss function and adding it to the objective function. This confirms that dual discriminator is capable of producing more natural looking images after UIE processing.

CONCLUSIONS

In the present work we demonstrated the realization of the NNUIE-GAN which is capable of producing more natural looking underwater enhanced images. It is a Generative Adversarial Network based model developed for enhancing the quality of the underwater images in real time. For generator a U Net based architecture with fewer parameters is tailored which made real time image enhancement process possible. Moreover, dual discriminator designed drives generator at local level details and produce more natural looking images. For this we carefully crafted loss functions.

These loss functions contributed to objective function thereby refraining it from overexposing but at the same time effective colour consistency and hue rectification is introduced in enhanced images. The validity of tailored loss functions is verified by qualitative and quantitative analysis of produced results. The results confirmed that, NNUIE-GAN can eliminate colour deviations and improve image clarity which are known as primary characteristics that enhance the visual perception. Therefore, visual perception of underwater images can be improved using NNUIE-GAN model.

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