

NEW APPROACH TO UNDERWATER IMAGE
ENHANCEMENT USING MODIFIED RESIDUAL BLOCKS
IN GENERATOR ARCHITECTURE FOR IMPROVED
CYCLE GENERATIVE ADVERSARIAL NETWORKS

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Received on August 27, 2023

Presented by Ch. Roumenin, Member of BAS, on November 28, 2023

Abstract

Images captured underwater frequently have a low resolution as a result of a number of issues including light attenuation, backscattering, and colour distortion. The restoration of underwater images, which serves as an essential building block for the field of underwater vision research, remains a difficult endeavor. The process of removing the haziness and the colour distortion caused by the underwater environs is the main focus of the work that goes into the restoration of underwater images. Within the confines of this research, we present an enhanced approach for the enhancement of underwater images called Improved Cycle GAN (Generative Adversarial Network). The suggested approach makes use of a dual architecture that is composed of a generator network and a discriminator network in order to learn the mapping between low-quality underwater photographs and high-quality images. This dual architecture is comprised of a generator network and a discriminator network. The generator network is trained to transform the input image into an enhanced image, while the discriminator network evaluates the realism of the generated images. The suggested method outperforms state-of-the-art visual quality methods on a real-world UFO underwater image dataset. The proposed method is used to recover the original image. In order to measure quantity, the underwater image quality measure attributes called underwater image colourfulness measure (UICM), underwater image sharpness measure (UISM), and underwater image contrast measure (UIConM) are assessed. The proposed method could

be employed in various underwater imaging processing applications, such as underwater surveillance, marine biology research, and underwater exploration, where high-quality images are crucial for effective analysis and decision-making.

Key words: image processing, underwater vision, image quality measure, improved cycle GAN, image restoration

Introduction. The importance of underwater vision has recently been recognized by several sectors, including industry, the military, scientific studies, aquatic life protection, and underwater pipeline monitoring. There are a lot of riches in the ocean, and not all of them have been used up yet. The ocean's underwater ecology is more complicated than that of lakes, rivers, and other bodies of water. Due to this, there is an unacceptable level of danger involved in artificially exploring and developing the ocean. Visual pictures are a big part of how an autonomous underwater vehicle (AUV) learns about and understands the environment it is in [1].

Autonomous underwater vehicles (AUVs) are now important tools for humans to learn more about the ocean. Most of the time, raw images of underwater environments are not enough for research. Because the water absorbs and scatters light, photos taken underwater finally come out with distorted colour schemes, poor contrast, and a lot of noise. The ocean can take in orange and red light faster than it can take in blue and green light. Underwater photos are generally blue-green. Both absorption and scattering can be attributed to the presence of water, which contains both microscopic floating particles and dissolved organic material. Due to the varying degrees to which the water's surface and its surroundings filter different wavelengths of light, images taken underwater usually have a bluish-green tint [2]. Underwater image restoration is challenging, yet it is necessary for a number of important areas of research and development, including finding and identifying underwater targets, underwater rescue, underwater robots, monitoring ocean creatures, real-time navigation, and mapping marine geology [3].

Due to seawater pollution, underwater image restoration is difficult and tricky [4]. Underwater vision research is vital for addressing seawater pollution challenges. It aids in environmental assessment, monitoring, and mitigation by enabling early detection of pollution events. The research contributes to restoration planning, fostering technological advancements for data collection in polluted underwater environments. Overall, it plays a crucial role in understanding and combating the impact of seawater pollution, guiding restoration efforts, and promoting sustainability for marine ecosystem preservation. Underwater image enhancement is particularly difficult owing to the uncertain and often variable ambient light [5]. Underwater images become less clear as a result of light scattering and absorption that is wavelength dependent [6]. This results in a reduction in contrast as well as visibility, and it also creates unsightly colour casts. In order to increase the quality of the underwater signal for display or analysis, methods known as underwater

image enhancement (UIE) are required. Some traditional ways [7] boost image quality by changing pixel values, while others [8,9] need a mathematical model of an underwater imaging system.

Traditional methods for repairing and enhancing underwater photographs must account for several aspects, including water's intrinsic qualities, making them difficult to implement [10]. Nevertheless, the issue of image deterioration that occurs due to a lack of light underwater cannot be fixed using these approaches. In underwater image improvement, the neural network-based GAN is most popular. We offer a solution that addresses all aspects of the problem from start to finish to speed up the process. Underwater Image Sharpness, Colourfulness, and Contrast measures determine underwater image quality. These metrics are called Underwater Image Contrast, Sharpness, and Colourfulness.

Literature survey. Underwater image enhancement improves RGB values and details. XIN and PENG [11] present an effective underwater picture enhancement GAN-based ResNet model. They eliminate batch normalisation (BN) after each convolution layer for quicker training and fewer artefacts. Also, smooth loss functions reduce halo effects. LAN et al. [12] report an effective unsupervised GAN for underwater picture restoration.

Image processing can dramatically reduce underwater distortions [13]. WANG et al. [9] propose a realistic underwater GAN (UWGAN) and use U-net loss techniques to fix ocean photos. GUO et al. [14] propose multiscale dense GAN to enhance underwater photos. This procedure restores colour and details. Underwater pictures can be restored by changing propagation line attenuation. LI et al. [10] corrected red channels and dehazed blue-green channels.

After success in computer vision, researchers used deep learning to enhance underwater imaging. SONG et al. [8] evaluated underwater ambient light and transmission with convolutional networks. Deep learning studies GAN image formation and translation. Underwater images were utilized in other GAN testing. FABBRI et al. [15] recommended underwater image quality for visual safety and dependability. Image feature fusion based on edge detection was proposed by LI et al. [16]. It extracts edge characteristics from pictures using HDE, Sobel, and deep learning. The approach addresses the issue of neural network-based visual feature extraction focusing more on texture than form, which reduces accuracy [17]. This approach improves picture classification and retrieval accuracy by integrating edge detection and deep learning.

Materials and methods. Because underwater images receive less light from the surroundings, they are darker than land-based images. The camera's extended exposure duration increases blur and noise during photo capture. Due to little or no colour and shape information, underwater photos make object segmentation difficult. Enhancing underwater images is a challenging task due to the attenuation and scattering of light as it passes through water, which results in degraded image quality. Generalised Adversarial Networks (GANs) have shown promise

in picture improvement. A unique Generative Adversarial Network (GAN), the “Improved Cycle GAN”, was created to achieve this goal. Generator and discriminator neural networks make up Generative Adversarial Networks (GANs). This technique is competitive, with the generator trying to create images that seem like actual ones and the discriminator trying to tell them apart. Cycle GAN is a type of GAN designed for image-to-image translation tasks. It is particularly useful for tasks like turning underwater images into clear, enhanced versions. Cycle GAN extends the basic GAN by introducing cycle-consistency constraints. Generator Networks: Improved Cycle GAN typically uses two generator networks: one for enhancing underwater images (underwater-to-clear) and another for the reverse transformation (clear-to-underwater). These networks learn to map images from one domain to another. Discriminator Networks: Two discriminator networks assess the realism of the generated images in each direction, providing feedback to the generators.

Image enhancement by improved cycle GAN. We enhance the Cycle GAN algorithm for low-light images. Cycle GAN [7] uses unpaired data from two domains to transform pictures. Additionally, two forward and reverse models translated unpaired data image-to-image. This strategy ensured that the source and destination domains shared solely picture aesthetics. The original picture or “source domain” was preserved. To use our new and improved Cycle GAN, we must make low-light pictures more colourful and distinct. Therefore, the database with low light would operate best as the source domain and the database with high light as the objective domain.

This section will investigate the architecture of the original Cycle GAN generators and our upgraded ones, then compare and contrast them. Generator and discriminator models in GANs employ adversarial learning to improve each other. These innovations streamline GAN collaboration. This technique must be repeated multiple times until completion. GANs were used to create Cycle GAN to modify images [7]. The Cycle GAN system’s two generators and discriminators aim to provide domain-independent, two-way picture translation.

The encoder reduces features map size using three layers: a 7×7 convolution layer, two stride-2 layers, and a stride-1 layer. The first and two encoder layers have 7×7 filters. The first and stride-2 convolutional layers feature 7×7 filters. Figure 1 depicts 9 feature map residual blocks. Two-deconstruction decoder Hidden. Transposed convolution extends layer feature maps. View from behind. An output layer creates a synthetic image with the same aspect ratio. Improved Cycle GAN translated unpaired pictures. Despite studying low-light photos, we updated the Cycle GAN generator to generate a new network. Figure 2a shows our improved Cycle GAN, while Table 1 provides generator and discriminator properties. The updated Cycle GAN generator features two changes. The activation function first deviates. Previous model’s updated linear unit activation function harmed low-light input images. A new model activation function. Most

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Comparison analysis

Description	Colourfulness measure (UICM)	Sharpness measure (UISM)	Contrast measure (UIConM)	Quality measure (UIQM)
Raw	0.5432	6.7291	0.4470	3.6596
DCP	1.2385	6.6084	0.5447	4.0263
DGAN	1.1448	6.7567	0.5584	3.5574
UGAN	0.9217	6.4660	0.4602	4.1255
Water GAN	1.3423	6.6737	0.4747	3.8065
Cycle GAN	3.1848	6.7938	0.6378	4.3761
Imp Cycle GAN	4.1866	7.0029	0.7179	4.7527

low-light photographs have poor pixels $[-1, 1]$. Low-light photos have few pixels. ReLU may return low-pixel-value picture data, making training challenging. Thus, we advised replacing all changed Cycle GAN generator activation functions with leaky ReLU (LReLU) to decrease information loss, shape change, and learning instability.

We then altered the generator's residue block, a machine element. Figure 2a, b compares our improved Cycle GAN residual block design to the original. We upgraded Cycle GAN with these parts. The original Cycle GAN residual block has two 3×3 -modified 256-dimensional convolutional layers.

Block input and output are combined in shortcut structures. Instead, our updated Cycle GAN residual block contains 2×1 and 3×3 convolutional layers. Bottom-to-top layer order. Four convolutional layers and a bottleneck-like design

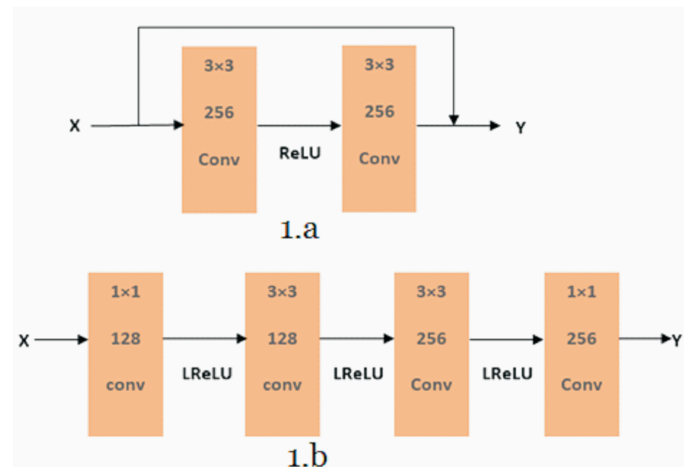


Fig. 1. a. Residual blocks in actual Cycle GAN; b. Residual blocks in modified Cycle GAN

make up the new residual block (Fig. 2b). New residual block contains this block. It features 128 channels, unlike prior designs with 256. The same methods removed five of the nine original blocks. The Cycle GAN model features various residual block size and composition. It increases image quality at low computational cost and processing time.

Results and discussion. This study uses experimental UFO data. Md Jahidul Islam provided UFO-120 paired and unpaired picture samples. We shall take turbid and clear underwater images during our inquiry (Y). The training

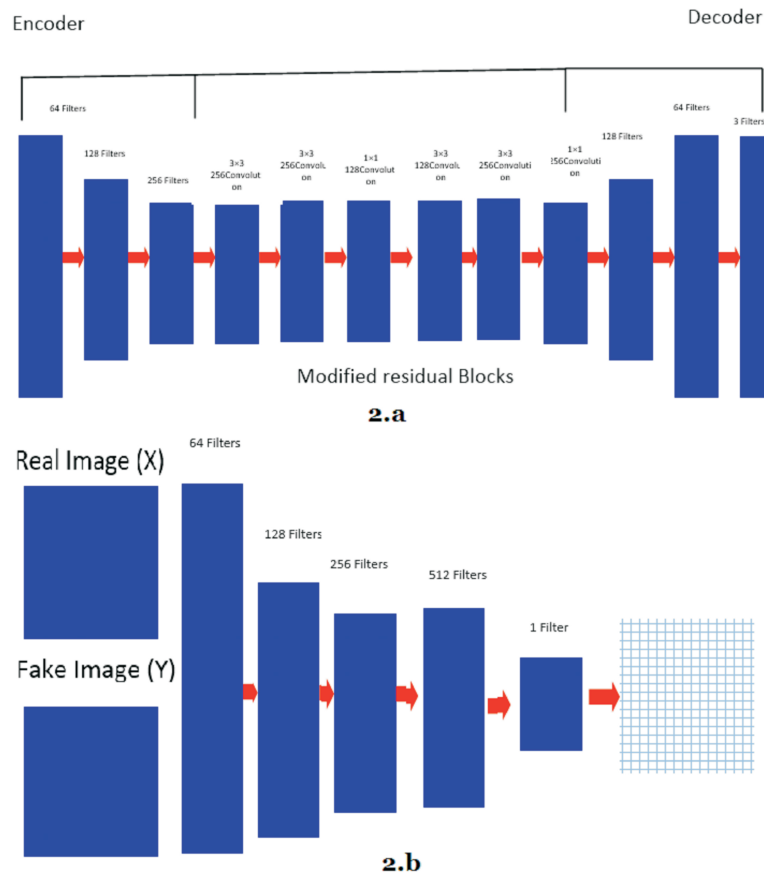


Fig. 2. a. Generator architecture of Imp Cycle GAN; b. Discriminator architecture of Imp Cycle GAN

dataset features 850 of 1050 foggy underwater photographs, whereas the test dataset has 200. In folder X, we photographed 341 Jiao Zhou Bay scenarios. UFO-120 captured 496 natural scenes [19]. Both photo sets are in X. The test dataset comprises 180 real and 80 fake photos. The Y dataset comprises 2500 pictures. The internet provides the Y dataset. We plan to replicate the underwater images by changing the visual style of the hazy dataset X into the clear dataset Y using our model. This will help us see what is in the photographs. Figure 3 exhibits photos from our processing datasets. Our datasets include a wide range of circumstances, demonstrating our ability to generalize. The underwater photos were taken in various conditions. Images improved by an algorithm are shown in Fig. 3. Figure 3 illustrates our improved Cycle GAN method which outperforms previous underwater vision analysis techniques.

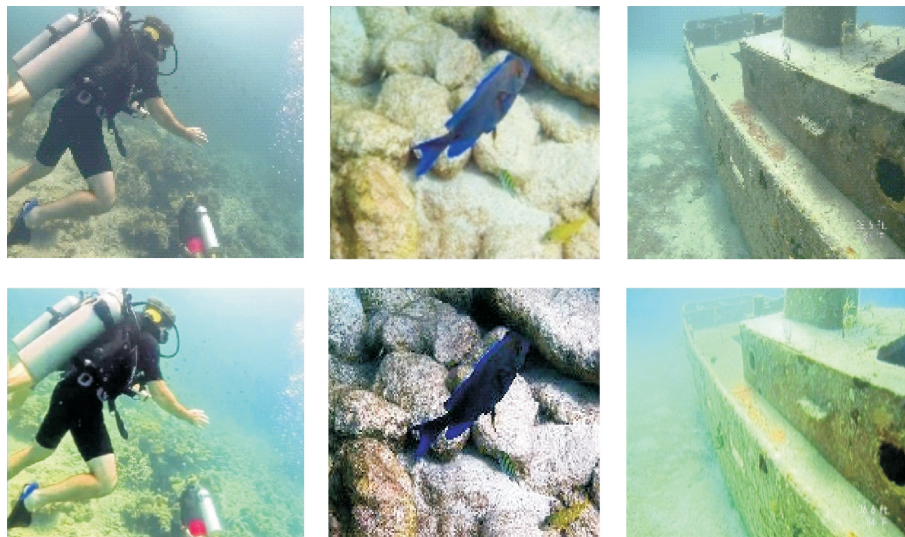


Fig. 3. Original image vs. enhanced image by Imp Cycle GAN

Table 1 shows the mean of results from several approaches and the most favourable results on our test dataset.

Conclusion. Water absorption, scattering, and turbulence diminish underwater photos. This study investigated improving Cycle GANs for underwater photos. We found that the enhanced Cycle GAN increased underwater image quality, including colourfulness, sharpness, and contrast. This shows that Improved Cycle GANs can improve underwater image quality. The revised Cycle GAN included paired L1 and L2 losses, which changed the generator structure of the original Cycle GAN. This improved augmentation quality and reduced processing time and cost. Because of this, the Under Water Image Quality has a higher correlation with human visual perception than other quality measures used in existing algorithms for processing underwater images, and it measures underwater image

quality comprehensively and exhaustively. The UFO-120 database photographs were assessed using the data. The data show that our upgraded Cycle GAN algorithm improves underwater image perception more than earlier methods. Future investigations will address image segmentation. This finding has major ramifications for underwater imaging. Image quality can improve underwater ecosystem studies, item identification, and exploration. This study was limited by focusing on colourfulness, sharpness, and contrast. Further studies might examine colour balance and noise reduction as picture quality indicators. Our work shows that Cycle GANs can increase underwater image quality. This research increases undersea exploration and emphasizes improved imaging.

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