Received: 9 March 2020 | Revised: 26 April 2020 | Accepted: 29 April 2020
DOI: 10.1002/cpe.5841

SPECIAL ISSUE PAPER

Underwater image enhancement using improved generative adversarial network

Tingting Zhang[1] | **Yujie Li**[2] | **Shinya Takahashi**[3]

[1]School of Information Engineering, Yangzhou University, Yangzhou, China
[2]Faculty of Engineering, Fukuoka University, Fukuoka, Japan
[3]Faculty of Engineering, Fukuoka University, Fukuoka, Japan

Correspondence
Tingting Zhang, School of Information Engineering, Yangzhou University, Yangzhou, China.
Email: yzyjli@gmail.com

Summary

The generative adversarial network is widely used in image generation, and the generation of images with different styles is applied to underwater image enhancement. The existing underwater image generative adversarial network does not realize color correction when processing underwater images Therefore, we propose an improved generative adversarial network for image color restoration. Firstly, the loss function in the network is improved to train the dataset. Then the improved network is used to detect the underwater image. After network testing, the underwater image is more satisfactory than the traditional image. Numerical results show that this method has a good color restoration and sharpening effects.

KEYWORDS
color restoration, GAN, image enhancement, loss function

1 | INTRODUCTION

Image is the carrier of information and one of the most intuitive tools for human beings to understand and explore the world. The ocean is a new resource location, but the marine environment is complex and unique, so humans need tools to understand it more clearly. Underwater images can directly reflect the ocean environment and the state of target objects, which can provide great help for human exploration of the ocean, development of resources and environmental protection. However, due to the absorption and scattering of light in water, color distortion and contrast reduction often occur in underwater images. In view of these problems, many researchers have proposed corresponding solutions and published a large number of literatures.

These solutions can be divided into two categories: traditional image enhancement methods and deep learning-based methods. Among them, the traditional image enhancement method is effective in underwater image processing, but there are some problems, which reduce the applicability of the method. Traditional image enhancement methods mainly focus on denoising and contrast enhancement, including histogram equalization,[1-3] Retinex algorithm,[4-6] dark channel prior,[7] etc. The ideal of histogram equalization is stretching the image pixel intensity distribution to enhance image contrast, but this method ignores the structural information of the image and produces an unreal effect in enhancing the image. The Adaptive Histogram Equalization algorithm (AHE) is to improve the image contrast by calculating the local histogram of the image and then redistributing the brightness. However, the algorithm will overamplify the noise in the same area of the image. By using the contrast adaptive histogram equalization[2] algorithm to limit the contrast of each small region and speed up the calculation by interpolation, this adverse amplification can be effectively limited.

Retinex algorithm is a classic image enhancement method, assuming that the image is composed of the incident and the reflected image. By removing or reduce the effects of the incident image, try to retain the nature of the reflected image of the object. Jobson et al[4] proposed a center-surround function based on Retinex. The center-surround function adopted low-pass function to estimate the low-frequency information in the image, remove the low-frequency information and retain the high-frequency information. Although the above two methods can achieve image defogging, there are also problems such as insufficient edge sharpening and color distortion. Zhang et al[6] underwater image enhancement method based on the Retinex algorithm is put forward, improve the brightness of the underwater image, its limitation is the loss of image detail. He et al[2] proposed an image defogging method based on a dark channel prior, which realized image defogging by refining the transmission map and estimating the ambient light. Its disadvantage lies in a large amount of calculation, easy to produce halo or double shadow in the local area. Drews et al[8] proposed an adaptive estimation method for underwater environment transmission based on dark channel priori. They observed and analyzed underwater images and found that blue and green channels were the source of underwater visual information. On this basis, they improved the dark channel prior algorithm to enhance the underwater image. Bazeille et al[9]proposed an underwater image preprocessing algorithm consisting of several continuous independent processing steps, including correction of nonuniform lighting (homomorphic filtering), noise suppression (wavelet denoising), enhanced edges (anisotropic filtering), and color adjustment (equalized RGB channel suppression of primary color).[10-13] It reduces the underwater disturbance and improves the image quality, but the processed image is generally fuzzy. Chambah et al[14]proposed a color correction method based on ACE (Adaptive Contrast Enhancement) model, and the ACE model was an unsupervised color equalization algorithm developed by Rizzi et al.[15] ACE is a perception method inspired by some adaptive mechanisms of the human visual system, especially brightness constancy and color constancy. When ACE is used in videos shot in water environment, the video presents a strong and uneven color due to the influence of water depth and artificial lighting. Therefore, Chambah adjusted the internal parameters of ACE algorithm to meet the natural requirements of image and histogram shape, and processed such water images. Although the color of the image was restored, there was a loss of detail.

In recent years, due to the great success of deep learning in other fields, the application of deep learning to image enhancement is also the research direction of many scholars in the field of image. Cai et al[16]developed a simple and powerful CNN-based SICE enhancer, which can adaptively generate high-quality enhancement results for a single over-exposed or under-exposed input image. However, when this method is applied to low-contrast images, the loss of image details exists. Salazar et al[17] proposed an improved image algorithm with a noise reduction effect, in which a multilayer perceptron was used to calculate the transmission map directly from the minimum channel, and contrast stretching technique was adopted to improve the dynamic range of restored images. However, the enhanced image is deficient in image defogging and color correction. Zhang et al[18]proposed an algorithm combining Retinex algorithm and multilayer perceptron for underwater image enhancement. Retinex was first used to preprocess the image, and then dark channel priors and multilayer perceptron were used to estimate the transmission map, so as to achieve underwater image enhancement, but the visual effect was not good.

In 2014, Goodfellow et al[19] proposed a new framework, a deep adversarial framework composed of generation network and discriminant network. The generator captures the distribution of data that it wants to pass the discriminator test, which estimates the probability that the sample is from a true distribution. The Generative Adversarial Network (GAN) framework was inspired by the "two-person zero-sum" game, where competition between generators and discriminators forced them to refine their methods until they could identify the fake from the real sample. In the training process,[20] the quality of the generated samples and the recognition ability of the discriminator are interactively improved. It is worth noting that the generator can be any algorithm as long as it can learn the distribution of the training data, while the discriminator needs to extract features and use them to train a binary classifier. Early GAN is difficult to control, easy to collapse, the results are not satisfactory. In view of the problems in the application process of this framework, many people have also made improvements in the later period to improve the effectiveness and applicability of the GAN.[21]

The researchers began to find solutions by improving the structure and training skills. At the same time, the application of GAN achieved good results, generating high-quality images and realizing the transformation of image style.[22] Although widely used, there are few theoretical explanations for the above problems in GAN. In the rising stage, Wasserstein GAN (WGAN)[23] analyzed in detail the causes of poor control and easy collapse of GAN, and proposed a solution to improve the quality of generated results. Therefore, many new models have been proposed from different perspectives, and better results have been obtained. DCGAN[24] combines GAN with CNN and performs well in the field of computer vision. It sets a series of restrictions on the CNNs network topology so that it can be steadily trained and used to classify images using the learned feature representation. In DCGAN, the author adopts the batch normalization (BN) algorithm[25] to solve the gradient disappearance problem. The BN algorithm solves the problem of poor initialization by passing the gradient to each layer and preventing the generator from converging all samples to the same point. Different activation functions are used to meet different needs. For example, ReLU activation function,[26] leaky ReLU activation function.[27] Li et al proposed WaterGAN,[28] a generator network for underwater image modeling, which is a novel generator network structure. The structure integrates the underwater image generation process to generate high-resolution output images and then uses the end-to-end model learning pipeline to correct color for the monocular underwater images and the generated images. But they need deep information when training networks and deep information is hard to attain. CycleGAN[22] is an unpaired image style conversion GAN proposed by Zhu et al, whose essence is two mirror-symmetric GAN, forming a ring network. Fabbri et al[23] proposed a method to enhance underwater color images by using the GAN and used the dataset of paired images generated by CycleGAN as the training set. Through training paired datasets, underwater image enhancement is realized. Although the underwater image restoration effect is close to the real land, the color is not natural. Yu et al[29] proposed underwater GAN, a conditional GAN for underwater image recovery. Taking WGAN with gradient penalty as the backbone network, the underwater image dataset was established, and the underwater image was generated by simulation, and the model was trained. Lu et al[30] proposed an underwater image recovery method based on multiscale cycle GAN, acquired image transmission map by dark channel prior algorithm, and designed selecting structural similarity (SSIM) loss to improve the quality of underwater image. Liu et al[31] proposed an underwater image enhancement algorithm based on the depth residual framework. Using CycleGAN to generate composite images as a training set, and then introducing the super-resolution reconstruction model into the underwater resolution application. Although the above two methods achieve image enhancement, the underwater image visual effect is not satisfactory.

In this paper, the contribution of the improved algorithm based on the underwater GAN proposed is as follows: the gradient difference loss (GDL) is used to sharpen the image to avoid image blur. The least square method is used to improve the quality of the generated image. Experimental results show that this method can achieve better enhancement results, restore image color, and enhance image detail.

2 | THE RELATED WORK

Goodfellow et al[19] inspired by the two zero-sum game theory, puts forward a GAN. The generation problem is considered as a game between the discriminator and the generator. The generator generates synthetic data from a given noise (usually a uniform or normal distribution), and the discriminator distinguishes whether the data comes from real data or the generator's output. The former tries to produce real data, and the latter, in turn, tries to distinguish real data from generated data as perfectly as possible. Thus, the two networks fight each other and advance each other. The data generated by the generator is becoming more and more perfect, just like the real data. Therefore, GAN can be used to generate the desired data (pictures, sequences, video, etc.). To solve the difficulty of GAN training, the loss of generator and discriminator cannot indicate the training process and the lack of diversity of generated samples.

Arjovsky et al.[32] proposed the implementation process of the improved algorithm WGAN. In this paper, the reason for training instability caused by generator gradient vanishing is expounded theoretically, and the Jensen-Shannon divergence is replaced by Wasserstein distance to solve the problem theoretically. Besides, WGAN also theoretically gives the reason for mode collapse for naive GAN and explains the superiority of WGAN in this aspect from the perspective of the experiment. Finally, Lipschitz constraint is derived from the distance between the generated distribution and the real distribution, relevant theories and Wasserstein distance. In theory, since there is Lipschitz-1 constraint on function (ie, discriminator), but this condition cannot be directly reflected in the neural network model, the author uses the clip as an approximate substitute for Lipschitz-1 constraint. However, the two conditions are not equivalent and usually lead to training failure. In this regard, Ishaan Gulrajani proposed WGAN with a gradient penalty (wgan-gp),[29] which regularizes the constraint of Lipschitz-1 and approximates the constraint condition of Lipschitz-1 by writing the constraint as the penalty term of the target function. In the form of regularization, the constraint of the discriminator is expressed, which also inspires the regularization model of GAN. Although WGAN and wgan-p have solved the problem of training failure, the training speed and convergence speed are slower than conventional GAN. The improved algorithm based on GAN mentioned above can realize image enhancement to a certain extent, but the problem of image generation distortion still exists when it is used to process underwater images. Therefore, based on the characteristics of underwater images, this paper improves the loss function, so as to achieve the purpose of generating images close to the real images.

3 | IMPROVED METHOD

In this paper, an improved loss-function method is proposed to generate a network that can be used to enhance underwater images, to achieve color correction and image sharpening. The flow chart is shown in Figure 1.

The generator network in the improved algorithm in this paper is a full convolutional encoder-decoder, similar to the design of a u-net struct[25] in Reference 23. The working principle of encoder-decoder network is to use convolution to down sample (encode) the input to low-dimensional embedding, and then use transpose convolution to embed up-sampling (decoding), so as to realize image reconstruction. Taking advantage of u-net, it is possible to obviously preserve the spatial dependencies generated by the encoder, as if relying on embedding to contain all the information. Each

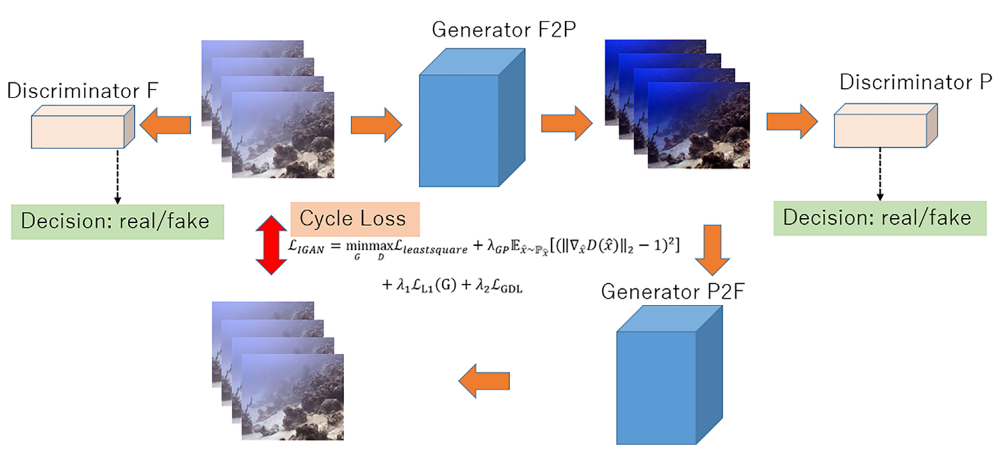


FIGURE 1 Flowchart of improved method.

convolutional layer of the generator has a kernel of 44 and a step size of 2. The operation after the convolution operation coding of the generator network is the batch normalization[14] and the leaky ReLU activation function with a slope of 0:2, while the operation after the decoder transpose convolution is the ReLU activation function,[15] and the last layer is the nonlinear hyperbolic tangent function matching the input distribution. The full-convolution discriminator in the algorithm is similar to the structure in Reference 21, and it is used for identification at the level of image patch.

3.1 | Adversarial Networks

Our network is constructed by the GAN,[19] The standard GAN consists of generator *G* and discriminator *D*. Let *z* be random noise and *x* be real data. Generator network and discriminator network can be represented by *G* and *D*, respectively, where *D* can be regarded as a binary classifier. Using cross-entropy, the basic model of GAN can be written as,

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim P_{\text{data}}}[\log D(x)] + \mathbb{E}_{z \sim P_z}[\log(1 - D(G(z))], \tag{1}$$

where P_{data} is the data distribution of the generator, $P_z$is the prior probability of input noise, $\log D(x)$ represents the discriminator's judgment of real data, and $\log(1 - D(G(z))$ represents the synthesis and judgment of data. Through such minimax games, *G* and *D* are alternately optimized to train the required generative and discriminant networks until the Nash equilibrium point is reached.

Since the objective function of original GAN generally uses cross-entropy, and cross-entropy as a loss, the generator will not optimize the generated images recognized as real images by the discriminator. Even if the generated images are far from the real images, which means that the image quality generated by the generator is not high. When the least square method is used as the objective function, to minimize the loss of the least square method, the generator has to pull the generated image far from the decision boundary to the decision boundary under the premise of deceiving the discriminator. Therefore, we use the least square method to improve image quality and restore image color. Its definition is shown in Equation (2):

$$\min_G \max_D V(D, G) = \frac{1}{2}\mathbb{E}_{x \sim p_{\text{data}}}[(D(x) - 1)^2] - \frac{1}{2}\mathbb{E}_{z \sim p_z}[(D(G(z)))^2]. \tag{2}$$

3.2 | Improved loss function

In the process of network training, weight is easy to update too fast, and weight changes greatly each time, leading to a weight explosion. Therefore, we add gradient punishment[29] to solve these problems, whose definition is shown in Equation (3):

$$\mathcal{L}_{\text{GP}} = \lambda_{\text{GP}} \mathbb{E}_{\hat{x} \sim \mathbb{P}_{\hat{x}}}[(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2]. \tag{3}$$

Including $\mathbb{P}_{\hat{x}}$ defined as from the real data distribution and generator between pairs of points along with a straight-line sample, λ_{GP} is a weighting factor, values to 10. In order to give G a sense of ground reality and capture low-level frequencies in images, Lipschitz-1 (L1) loss is also considered

$$\mathcal{L}_{\text{L1}} = \mathbb{E}_{\substack{x \sim P_{\text{data}} \\ z \sim P_z}}[\|x - G(z)\|_1]. \tag{4}$$

Finally, because generators usually produce blurry images, we found a strategy proposed by Reference 33 to sharpen the predicted gradient by directly punishing the difference between the predicted gradient of the generated image and the original image. α is an integer greater than or equal to 1, the GDL is given by

$$\mathcal{L}_{\text{GDL}}(x, G(z)) = \sum_{i,j} \||x_{i,j} - x_{i-1,j}| - |G(z)_{i,j} - G(z)_{i-1,j}|\|^{\alpha} + \||x_{i,j-1} - x_{i,j}| - |G(z)_{i,j-1} - G(z)_{i,j}|\|^{\alpha}. \tag{5}$$

Taking the above into account, we can get the objective function which we call improved GAN (IGAN),

$$\mathcal{L}_{\text{IGAN}} = \min_G \max_D \mathcal{L}_{\text{least square}} + \lambda_{\text{GP}} \mathbb{E}_{\hat{x} \sim \mathbb{P}_{\hat{x}}}[(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2] + \lambda_1 \mathcal{L}_{\text{L1}}(\text{G}) + \lambda_2 \mathcal{L}_{\text{GDL}}, \tag{6}$$

where $\lambda_1 = \lambda_2 = 1$.

4 | EXPERIMENTAL RESULT AND IMAGE QUALITY EVALUATION

We used several subsets of ImageNet[25] to train and evaluate our methods, and test images taken in real environments. This paper randomly selected 10 Zhang's enhancing images, IGAN generation results, and UGAN generation results for comparison. SSIM index[34] and Underwater Image Quality Measures (UIQM)[26] as evaluation methods.

SSIM is a model based on perception, which will be used as image degradation is perceived changes in the structure information, contains the important perceptual phenomenon at the same time, including luminance masking and contrast masking structure information, is to point to have a strong interdependent relationship between pixels, especially when they are spatially close to these dependencies contains important information about the structure of the object. The SSIM formula is based on three comparison measurements between the sample of x and y: luminance (l), contrast (c), and structure (s). The individual comparison functions are:

$$l(x, y) = \frac{2\mu_x\mu_y + c_1}{{\mu_x}^2 + {\mu_y}^2 + c_1} \tag{7}$$

$$c(x, y) = \frac{2\sigma_x\sigma_y + c_2}{{\sigma_x}^2 + {\sigma_y}^2 + c_2} \tag{8}$$

$$s(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}, \tag{9}$$

where μ is the average, σ^2 is the variance, σ_{xy} is the covariance of x and y, $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$, $c_3 = \frac{c_2}{2}$, L is the dynamic range of the pixel values, setting k_1, k_2 to 0.01 and 0.03 individually.

SSIM is then a weighted combination of these measures:

$$\mathrm{SSIM}(x, y) = [l(x, y)^\alpha \cdot c(x, y)^\beta \cdot s(x, y)^\gamma] \tag{10}$$

where, setting the weights α, β, γ to 1, the formula (10) can be reduced to the following form:

$$\mathrm{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{({\mu_x}^2 + {\mu_y}^2 + c_1)({\sigma_x}^2 + {\sigma_y}^2 + c_2)} \tag{11}$$

UIQM is a new nonreference underwater image quality measure, it comprises three measures: color, sharpness, and contrast. Each method can be used independently for specific underwater image processing tasks. Some VHS features, such as brightness and contrast masking, color perception, and relative contrast sensitivity, were incorporated into the measurement formulas. Therefore, compared with other existing methods for measuring underwater image quality, UIQM has a stronger correlation with human visual perception and can measure underwater image quality completely, comprehensively and effectively. The underwater image quality measure is then given by

$$\mathrm{UICM} = -0.0268\sqrt{{\mu^2}_{\alpha_1 \mathrm{RG}} + {\mu^2}_{\alpha_1 YB}} + 0.5186\sqrt{{\sigma^2}_{\alpha_1 \mathrm{RG}} + {\sigma^2}_{\alpha_1 \mathrm{YB}}}, \tag{12}$$

where, RG = $R - G$, YB = $Y - B$. μ is the asymmetric alpha-trimmed mean, it is close to zero means the better the white balance. σ^2 is the statistic variance, it demonstrates the pixel activity within each color component.

$$\mathrm{UISM} = \sum_{c=1}^{3} \lambda_c \mathrm{EME}(\text{grayscale edge}_c) \tag{13}$$

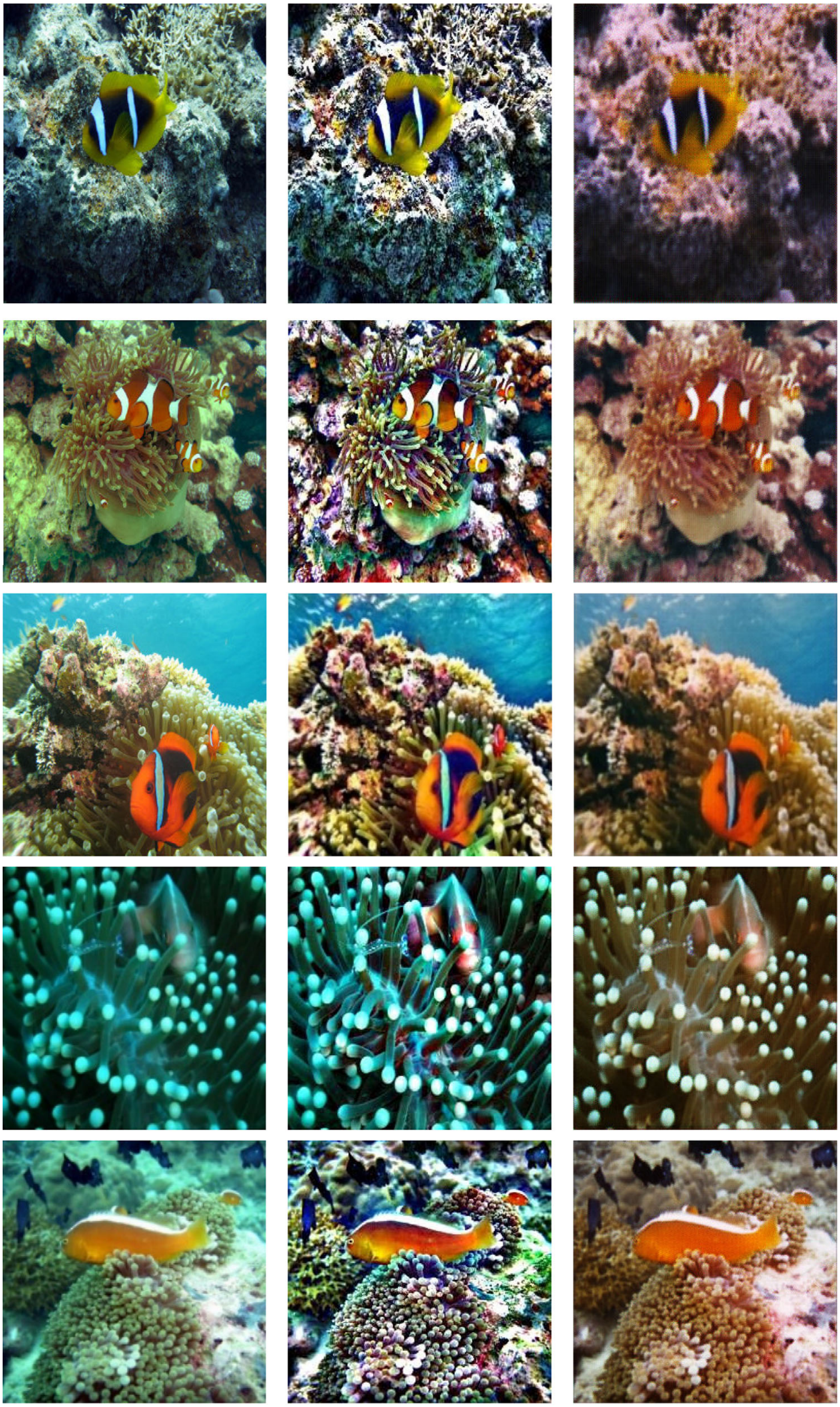
where the enhancement measure estimation (EME) is used to measure the sharpness of edges. $\lambda_R = 0.299$, $\lambda_G = 0.587$, $\lambda_B = 0.114$ are used to the relative visual response of the red, green, and blue channels.[20]

$$\mathrm{UIConM} = \mathrm{logAMEE}(\mathrm{Intenity}) \tag{14}$$

TABLE 1 Comparison of mean values of SSIM and UIQM

	Zhang[18]	UGAN	IGAN
SSIM	0.647506	0.8332507	**0.8443432**
UIQM	1.515455	1.532719	**1.54751**

Abbreviations: SSIM, Selecting structural similarity; UIQM, Underwater Image Quality Measures.



(A) original (B)Zhang[10] (C)UGAN

FIGURE 2 Samples from ImageNet dataset[32]

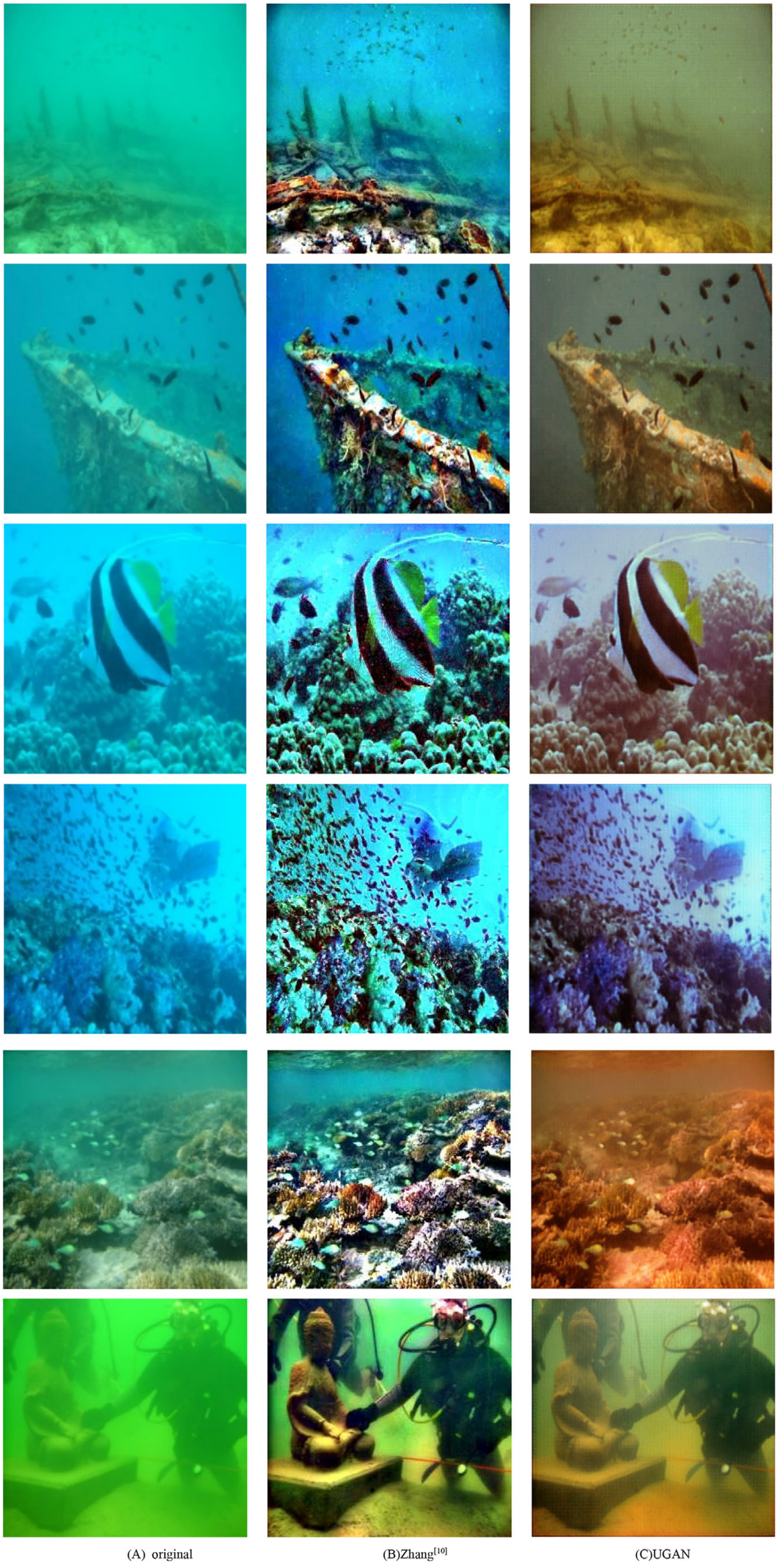


FIGURE 3 Samples from real underwater scene data sets

where AMEE introduces an entropy-like algorithm to the traditional Agaian entropy enhancement measure, which is expressed as the average Michelson contrast of the local area of the image.

By integrating the above three methods, UIQM quality evaluation method is obtained:

$$\mathrm{UIQM} = c_1 \times \mathrm{UICM} + c_2 \times \mathrm{UISM} + c_3 \times \mathrm{UIConM} \tag{15}$$

where, $c_{1,} c_{2,} c_3$ are application-dependent parameters, and the selection of these parameters depends on individual requirements. In this article, setting $c_1 = c_2 = c_3 = 1$.

Firstly, to fairly compare the improved method with the underwater GAN, we randomly selected 10 images from the generated results. Test each picture with SSIM and UIQM. Meanwhile, 10 images enhanced by Zhang algorithm were selected. SSIM and UIQM were used to test each picture and calculate the mean value of SSIM and UIQM of 10 pictures. By comparing the mean value, we can see from Table 1 that the method we proposed is 0.01 higher than UGAN in numerical value. According to the quality evaluation results of 10 pictures, our proposed improvement method is better than UGAN. Since the images are randomly selected, this conclusion is also true for the entire dataset.

Next, we evaluate the quality of our proposed method from the perspective of visual perception. The three groups of *a*, *b* and *c* in Figures 2 and 3, respectively, represent the original figure, the enhancement result of the algorithm proposed by Zhang and the enhancement result of IGAN. It can be seen that due to the absorption of light in the water, the underwater picture is blue and green. The result of the enhanced algorithm proposed by Zhang is too colorful and does not meet the requirements of human vision. The IGAN we proposed restored the color of the image to a large extent, making the image look like it was taken in the air.

The image in Figure 3 was taken in a real environment. From the perspective of the image, the algorithm proposed by Zhang has a good effect on image deblurring, but the color is too rich and the visual effect is not good. From the second image, the third image, and the last image, IGAN removes image blur to make the image clearer. In terms of visual effects, IGAN's enhancement results are more in line with human needs than those of Zhang's method.

5 | CONCLUSION

In this paper, an improved method based on an underwater GAN (IGAN) is proposed to enhance the underwater image. By referring to the structure of UGAN, improving the loss function in the network to recover the color of the underwater images and make the image closer to the real one. When restoring the image color, the GDL is considered to ensure that the generated image will not be blurred. From the perspective of numerical analysis, the enhancement effect of IGAN is 0.01 higher than that of UGAN. From the image, IGAN restored the color of the underwater image, giving the image the effect of shooting in the air. The blurred underwater image is deblurred to improve the contrast. However, in some images, IGAN's processing effect is flawed, such as color deepening and image resolution decline.

ORCID

Yujie Li https://orcid.org/0000-0002-0275-2797

REFERENCES

1. Acharya T, Ray AK. Image processing - principles and applications. *J Electron Imag*. 2005;15(3).1–15.
2. Pisano ED, Zong S, Hemminger BM, et al. Contrast limited adaptive histogram equalization image processing to improve the detection of simulated spiculations in dense mammograms. *J Digit Imag*. 1998;11(4):193-200.
3. Chambah M, Semani D, Renouf A, Courtellemont P, Rizzi A. Underwater color constancy: enhancement of automatic live fish recognition. Paper presented at: Proceedings of SPIE Color Imaging IX: Processing, Hardcopy, and Applications; vol.5293, 2004:157-168.
4. Jobson DJ, Rahman Z-u. Properties and performance of a center/surround retinex. *IEEE Trans Image Process*. 1997;6(3):451-454.
5. Fan TH, Li CL, Ma X,et al. "An Improved Single Image Defogging Method Based on Retinex. Paper presented at: Proceedings of the 2017 2nd International Conference on Image, Vision and Computing (ICIVC); 2017:410-413; Chengdu.
6. Zhang T, Zhu W, Li Y, Chen Z, Zhang X, Chen L. Improved image enhancement method based on Retinex algorithm. In: Lu H, ed. *Cognitive Internet of Things: Frameworks, Tools and Applications ISAIR 2018*. Vol 810. IEEE; 2020:291-299.
7. He KM, Sun J, Tang XO. Single image haze removal using dark channel prior. *IEEE Trans Pattern Anal Mach Intell*. 2011;2011, 33(12):2341-2353.
8. Drews, P., Nascimento, E., Moraes, F., Botelho, S., & Campos, M. (2013). Transmission estimation in underwater single images. Paper presented at: Proceedings of the IEEE International Conference on Computer Vision Workshops; 825-830.
9. Ronneberger O, Fischer P, Brox T. U-net: convolutional networks for biomedical image segmentation. *Med Image Comput Comput Assist Intervent*. 2015;9351:234-241.
10. Rizzi A, Gatta C, Marini D. A new algorithm for unsupervised global and local color correction. *Pattern Recogn Lett*. 2003;24:1663-1677.
11. Radford A, Metz L, Chintala S. Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv: Learning; 2015.
12. Xu B, Wang N, Chen T, et al. Empirical evaluation of rectified activations in convolutional network. 2015;1–9. https://arxiv.org/pdf/1505.00853.
13. Cao YJ, Jia LL, Chen YX, et al. Recent Advances of Generative Adversarial Networks in Computer Vision. *IEEE Access*. 2019.7:14985–15006.

14. Ioffe S, Szegedy C. Batchnormalization: accelerating deep networktraining by reducing internal covariate shift. In: Bach F, Blei D, eds. *Proceedings of the 32nd International Conference on Machine Learning*. Vol 37. Lille, France: JMLR Publisher; 2015:442-456.
15. Nair V Rectified linear units improve restricted boltzmann machines. Paper presented at: Proceedings of the 27th International Conference on Machine Learning (ICML-10); 2010:807-814.
16. Cai JR, Gu S, Zhang L. Learning a deep single image contrast enhancer from multi-exposure images. *IEEE Trans Image Process*. 2018;27(4):2049-2062.
17. Salazarcolores S, Cruzaceves I, Ramosarreguin J. Single image dehazing using a multilayer perceptron. *J Electron Imag*. 2018;27(04):1-12.
18. Zhang T, Li YJ, Li Y, et al. Underwater Image Enhancement Using Retinex and Multilayer Perceptron.ISAIR; 2019.
19. Goodfellow I, Pouget-Abadie J, Mirza M, et al. Generative adversarial nets. *Adv Neural Inf Process Syst*. 2014;2:2672-2680.
20. Pratt WK. *Digital Image Processing*. New York, NY: Wiley; 1991:2.
21. Liu P, Wang G, Qi H, Zhang C, Zheng H, Yu Z. Underwater image enhancement with a deep residual framework. *IEEE Access*. 2019;6:94614-94629.
22. Zhu JY. Unpaired image-to-image translation using cycle-consistent adversarial networks. *Int Conf Comput Vis*. 2017;1 2242-2251.
23. Fabbri C, Islam J, Sattar J. Enhancing underwater imagery using generative adversarial networks. Paper presented at: Proceedings of the International Conference on Robotics and Automation; 2018:7159-7165.
24. Creswell A, White T, Dumoulin V, et al. Generative adversarial networks: an overview. *IEEE Signal Process Mag*. 2017;35(1):53-65.
25. Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. ImageNet: a large-scale hierarchical image database. Paper presented at: Proceedings of the 2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2009); 2009; Miami, Florida; IEEE.
26. Panetta K, Gao C, Agaian S. Human-visual-system-inspired underwater image quality measures. *IEEE J Oceanic Eng*. 2016;41(3):541-551.
27. S. Bazeille, I. Quidu, L. Jaulin, and J. P. Malkasse. Automatic underwater image pre-processing. Paper presented at: Proceedings of the Caracterisation du Milieu Marin (CMM 06); 2006.
28. Li J. WaterGAN: unsupervised generative network to enable real-time color correction of monocular underwater images. 2017.
29. Gulrajani, Ishaan, Ahmed, F., Arjovsky, M., Dumoulin, V., & Courville, AC. Improved training of Wasserstein GANs; 2017. arXiv: Learning.
30. Yu X., Qu Y., & Hong M.. Underwater-GAN: Underwater image restoration via conditional generative adversarial network. Paper presented at: Proceedings of the International Conference on Pattern Recognition; 2018:66-75; Springer, Cham.
31. Lu J, Li N, Zhang S, Yu Z, Zheng H, Zheng B. Multi-scale adversarial network for underwater image restoration. *Opt Laser Tech*. 2019;110:105-113.
32. Arjovsky M, Chintala S, Léon B. Wasserstein GAN; 2017.
33. Mathieu M, Couprie C, LeCun Y. Deep multi-scale video prediction beyond mean square error; 2015. arXiv preprint arXiv:1511.05440.
34. Zhou W, Bovik AC, Sheikh HR, et al. Image quality assessment: from error visibility to structural similarity. *IEEE Trans Image Process*. 2004;13(4):600-612.

How to cite this article: Zhang T, Li Y, Takahashi S. Underwater image enhancement using improved generative adversarial network. *Concurrency Computat Pract Exper*. 2020;e5841. https://doi.org/10.1002/cpe.5841