Improved Underwater Image Enhancement Model Based on Atomization Images Model and Deep Learning

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***Abstract*—Underwater image enhancement has been widely used and received increasing attention. However, visual perception is affected by environmental factors, which reduces the visual quality. These images often suffer from color distortion, low contrast, and lack of detail, and the color of the image turns green or blue. This paper proposes an underwater image enhancement method based on deep learning and establishes a neural network based on dilated convolution and parameter correction. Firstly, multi-scale features are extracted, and then global features are used to enhance local features at each scale. In addition, the innovative CBAM attention mechanism is introduced. The algorithm is significantly faster than ICM, RGHS, UCM, CLAHE, HE, etc., in terms of operation speed. Besides, better computational performance, color correction, and detail retention are obtained.**

Keywords—underwater image enhancement method, CBAM, deep learning, convolutional neural network, extended convolution, multi-scale convolution kernel, underwater robot

I. INTRODUCTION

Combined with the latest revised physical imaging model proposed by AKKAYNAK et al. [1], this paper improves the existing deep learning-based image enhancement methods and proposes a new underwater image enhancement algorithm to solve the above problems effectively. The algorithm includes a background light estimation module and a transmission image estimation module based on a convolutional neural network. The output of these two modules is reconstructed with the input image to obtain an enhanced underwater image. When constructing the neural network, this paper is used the linear unit with parameter correction (PReLU) [2]. The dilated convolution operation (DILATED CONVOLUTION) [3] is used to improve the fitting ability of the network. In addition, experiments are carried out on the UIEB [4] dataset to verify the effectiveness of our algorithm. This paper compared five state-of-the-art algorithms such as CLAHE[5], HE[6], ICM[7], RGHS[8], and UCM[9], and various data and indicators are analyzed. Besides, the innovative introduction of the attention mechanism makes the algorithm in this paper outperform other traditional deep learning image enhancement algorithms in terms of SSIM and UIQM when dealing with clear images. Although the image quality is slightly reduced when dealing with blurred images, it still has advantages or comparability compared with other algorithms. The indicators exceed the average level of general algorithms.

The detection and recognition of small underwater targets based on optics is the key to the intelligent operation of underwater fishing robots. However, underwater target detection and recognition technology based on optical vision also face enormous challenges. The main reason is that the underwater images obtained by the visual vision system are seriously degraded due to the complex imaging environment of the ocean. The color deviation caused by light absorption, the blurring of details caused by forwarding scattering of light, and the low contrast caused by backscattering of light, make underwater images appear to have color decay, low contrast, and blurred details [10-11]. More importantly, there is currently no suitable image enhancement algorithm that can quickly and accurately identify and enhance underwater images captured by underwater robots. Images processed by CLAHE[5], HE[6], ICM[7], RGHS[8], and UCM[9], image enhancement algorithms cannot fully meet the existing requirements in terms of contrast and sharpness and often appear blurred and greenish. Another critical point is highlighted that the image enhancement speed of the current enhancement algorithm is slow and cannot quickly identify underwater images. Therefore, it is found that conducting related research on underwater image enhancement algorithms is substantial. In this paper, we will develop an image enhancement algorithm that is fast in operation and has significant visual effects on processed images.

Firstly, due to the absorption of light by water, the light will decay in energy during the transmission process. In general, red light decays the fastest in water, and blue-green light decays the slowest. Scattering can also cause poor imaging of underwater images. There are two types of scattering, forward and reverse. Forward scatter is the reflection of light from an object in the water onto the camera at a small deviation from the original direction of emission. Backscattering implies that when light irradiates the target object and encounters impurities in the water, light is scattered due to the presence of impurities and is directly received by the camera, resulting in low image contrast [12].

Traditional image enhancement methods are mainly divided into two parts: spatial domain image processing and frequency domain image processing. The spatial image processing method directly targets the pixels of the image by improving the gray level based on gray mappings. The industry's techniques generally include histogram equalization, limited contrast histogram equalization, grayscale world assumption, etc. In addition, removing image noise by filtering can also achieve the purpose of image enhancement. Median filtering, mean filtering, and other methods can meet such aims. The frequency domain image enhancement method indirectly enhances the image through various frequency domain transforms, such as Fourier transform, wavelet transform, and other methods. Many scholars at home and abroad have used spatial and frequency domain methods to enhance underwater images. Traditional image enhancement algorithms can eliminate image blur and enhance edges to a certain extent, but there is still significant noise, low definition, and color distortion. Therefore, it needs to be further strengthened and improved.

Recently, there have been two main processing methods for enhancing or restoring underwater images: one is used based on non-physical image enhancement methods, and the other is investigated according to solid mode restoration. On this basis, an underwater image restoration algorithm based on the entity model is proposed. This method can obtain an ideal non-degraded image by inverting the degradation of the image, which is a method of image restoration. The underwater image restoration technology is referred to as a physical model, which means building a reasonable mathematical model for the degradation process of the underwater image to estimate the model parameter information. Besides, it could help us understand the degradation process of the entire image to restore the underwater image to the state before degradation. Image restoration technology has a broader range of applications but often requires scene prior information or depth information to achieve image restoration.

II. Physical Imaging Mode

A. Influence of underwater environment on optical imaging quality

When taking photos in the underwater environment, the image quality is affected by light absorption, scattering, and refraction [13-14]. Due to the absorption of light by water, the light will decay in energy during transmission. As shown in Fig. 1., red light with a longer wavelength attenuates the fastest in water, and blue-green light with a shorter wavelength decays the slowest, which results in a greenish and bluish image taken underwater.

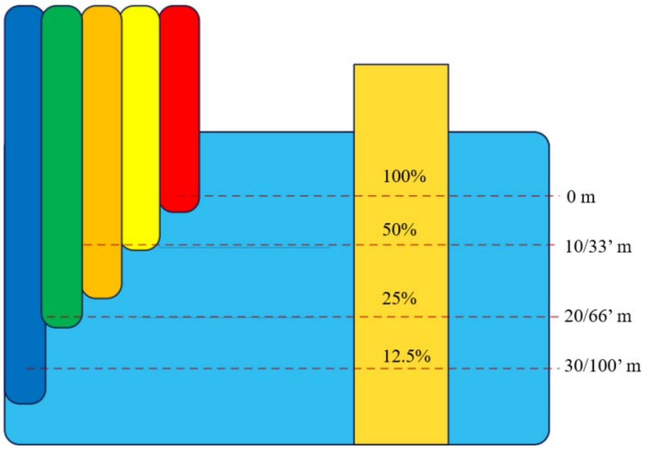

Fig. 1. The absorption of light of different wavelengths underwater

Affected by the absorption effect, the light of each wavelength is weakened as the depth becomes much deeper. Therefore, image acquisition in the deep sea usually requires artificial light supplementation or with the help of algorithms such as weighted fusion of multi-exposure image sequences to enhance exposure [10-11].

Fig. 2. shows the underwater imaging system. Among them, light scattering is divided into forwarding scattering and backscattering. The forward scattered light is reflected by the target surface or radiated into the imaging system after being scattered by suspended particles in the water [14], which will cause the image obtained by the imaging system to appear blurred. Backscattered light as the natural light incident on the water body and the light that enters the imaging system after being scattered by suspended particles [15] will cause the image acquired by the imaging system to present a phenomenon of low contrast. Using an artificial light source to actively illuminate the underwater imaging process can improve the above phenomenon to a certain extent. However, the light intensity of the artificial light source is gradually attenuated in the radial direction with the most critical point as the center, which will cause background gray in the acquired image. In addition, artificial light sources can play a minimal role in turbid water [16].

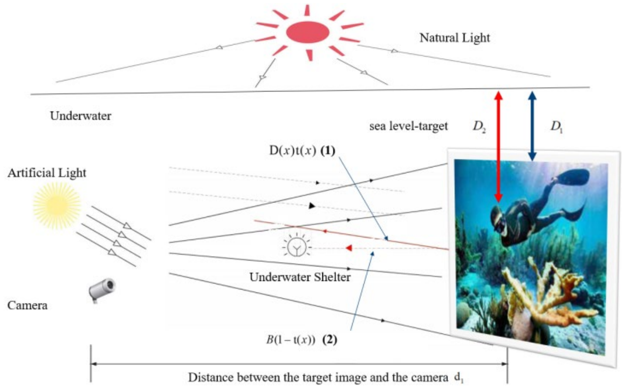

Fig. 2. Schematic diagram of underwater image blur and distortion

The optical imaging mode of underwater images includes two aspects: one is the direct transmission light, and the other is the background light. It can be seen from Fig. 2. that the directly transmitted light comes from the subject and will be attenuated during the propagation process. The main cause of color distortion in underwater images is the attenuation effect caused by the absorption and scattering of light [12]. The background scattered light is not emitted from the object, which is obtained by scattering many water particles into the surrounding environment. Light scattered by the background is the main reason underwater images' reduced contrast [17].

Light refracts in non-uniform media, which affects the straight-line transmission of light and causes distortion and distortion of details in the image [18]. Particles in the water, fluctuations in the seawater, and air bubbles in the water will cause light refraction, resulting in distortion of underwater images. Since the restoration of distortion is the category of image restoration, the method described in this paper belongs to image enhancement. It only addresses the problems of color distortion, contrast reduction, and blurred details caused by optical absorption and light scattering.

B. The mathematical expression of the underwater image imaging model

According to the imaging model of the underwater image captured by the robot [19], the approximate underwater image imaging model is as follows:

$$I(x) = D(x)t(x) + B(1 - t(x)) \tag{1}$$

x is the coordinates of each independent pixel of the object to be photographed. $I(x)$ represents the optical imaging image of the underwater image of the icon image $D(x)$ represents the radiant light emitted by the target object after being illuminated by the light source, which is the underwater image obtained after excluding the main interference factor background scattered light. $t(x)$ is the direct mapping of the reflected or radiated light of the underwater target. B is the natural underwater light not absorbed or attenuated by water when taking the image. $D(x)t(x)$ is the directly transmitted light reflected by the target object in the image to the image $I(x)$. $B(1-t(x))$ corresponds to the background scattered light formed by the reflection or refraction of underwater unattenuated natural light by underwater objects or shelters.

This paper is used the imaging model of underwater images obtained after many underwater image enhancement experiments in Reference [20]. The model proposed after correcting the background scattered light caused by underwater objects or obscuring objects is approximated as formula (2).

$$D_C(x) = (I_C(x) - B_C)e^{\beta_C^D d} + B_C \qquad (2)$$

The underwater image enhancement algorithm and model proposed in this paper is mainly to eliminate the background scattered light, that is, to eliminate the influence of $B(1-t(x))$ as formula (1) on the final underwater image $I(x)$. This paper conducted a series of underwater image enhancement simulation experiments using PyTorch deep learning technology.

III. Image Enhancement Algorithm Integrating Deep Learning and Imaging Model

A. Algorithm Design Idea

The image enhancement algorithm in this paper combines the PyTorch deep learning technology to enhance the image of the imaging model components in Equation (2). This paper added a convolutional neural network and an attention mechanism to extract pixel feature points of the enhanced image at a smaller size for underwater image enhancement [21]. In addition, this paper added a linear unit with parameter correction (PReLU) [2] and a dilated convolution operation (DILATED CONVOLUTION) [3] to the convolutional neural network to promote its fitting ability to the network.

The main idea of this paper is to design an algorithm to calculate B_C, the unknown underwater natural light that is not absorbed or attenuated by water in Equation (2) and the parameters of the direct output light reflected from the target object to the imaging image $e^{\beta_C^D d}$. A background scattering module is constructed using the pixel information corresponding to the known underwater images to estimate the invariant underwater natural light B_C.

However, the $e^{\beta_C^D d}$ parameter values of the direct output light corresponding to each independent pixel in the image are different, which increases the computational difficulty.

Combining each pixel module of the neural network with the background light information B_C of the image will significantly reduce the calculation difficulty of the parameter $e^{\beta_C^D d}$ and increase the accuracy of the calculation result. The parameter $e^{\beta_C^D d}$ obtained by formula (2) is the reciprocal of $t(x)$ in formula (1). Moreover, multiplication calculation when bringing formula (2) into reconstruction operation can significantly speed up the back-propagation of the loss function in deep learning speed.

Therefore, the algorithm in this paper is shown in Fig. 3. First, the background scattered light module is estimated, and the global underwater natural light B_C is proposed. Secondly, the parameter $e^{\beta_C^D d}$ of the direct output light in Equation (2) is obtained using the B_C, and image $I(x)$ is used to estimate the direct transmission mapping module jointly. The received parameter $e^{\beta_C^D d}$ value can be combined with the natural underwater light B_C into formula (2) to obtain an enhanced image. This paper will detail the background scattering and direct transmission modules with attention mechanisms below.

B. Convolutional Block Attention Module

CBAM (Convolutional Block Attention Module) is a lightweight attention mechanism proposed in 2018 [21]. As shown in Fig.3., CBAM contains two independent sub-modules, CAN (Channel Attention Module) and SAM (Spatial Attention Module), which carry out attention on the channel and space, respectively. CBAM can save parameters and computing power and ensure it can be integrated into the existing network architecture as a plug-and-play module. Since traditional pooling loses much information, in this experiment, based on the parallel connection of global max pooling and global average pooling of CBAM, power pooling is connected in parallel to reduce the information loss rate and ensure the effect of network training. The input feature map is first generated through CAN to create the channel attention feature in this attention mechanism. Then the channel attention feature and the input feature map are multiplied element-wise to create the input features required by the SPA module. Input the new feature map into the SPA module to obtain the spatial attention feature, and multiply the spatial attention feature with the input features of the module to get the final generated feature map [21].

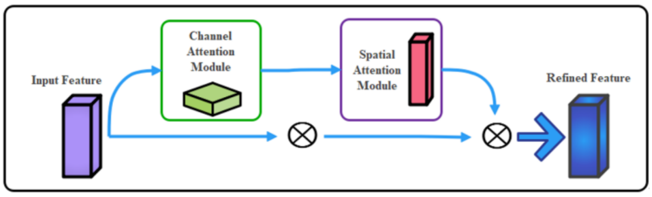

Fig. 3. The overview of CBAM

C. Background Scattering Estimation Module

The background scattering estimation module includes a set of convolution kernels of size 5×5 and a bunch of size 1×1, a global mean pooling layer, a collection of size 3×3 and a set of size 1×1 convolution kernel, and 1 CBAM module. The number of convolution kernels in each group is 3, and Fig. 4. shows the specific structure. The activation function of the convolution operation selects the parameterized rectified linear unit (PReLU) [4].

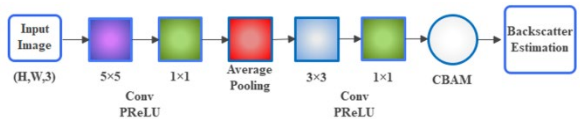

Fig. 4. Structure of backscatter estimation module

The mathematical expressions of the parametric rectified linear unit (PReLU) and the standard rectified linear unit (ReLU) are shown in equations (3) :

$$f_P(x)=\left\{\begin{array}{l} x,x\gg 0 \\ ax,others \end{array}\right\} \quad (3)$$

Compared with the common modified linear unit (ReLU), the advantage of using the modified linear unit with parameters is that it can avoid the phenomenon that the gradient is 0 when x is negative, resulting in the phenomenon that the corresponding parameters cannot be updated.

D. Direct Transfer Estimation Module

The direct transfer estimation module concatenates the background scatter estimation with the input image, and the subsequent operations include a set of 5×5, and a set of 3×3 dilated convolution kernels, a CBAM attention module, a collection of 3×3, and a bunch of 3×3 convolution kernels. A group of dilated convolution kernels of size 5×5 and a group of standard convolution kernels of size 1×1. The number of dilated convolution kernels in each group is 8. In addition, the number of the last set of standard convolution kernels is 3, as shown in Figure 5.

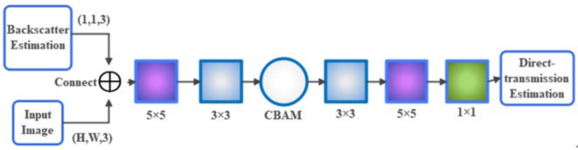

Fig. 5. Structure of direct-transmission estimation module

Dilated convolution can increase the receptive field by filling in additional 0s in the convolution kernel when the parameter quantity remains unchanged. A larger receptive field can help the network to use more image information to estimate the direct transmission parameters. This paper adopts the mixed dilated convolution design method to avoid the grid effect caused by dilated convolution, which means different dilation rates are selected for successive dilated convolution operations [17]. The expansion rates of this algorithm's three groups of dilated convolution kernels are 1, 2, 5, and 1, respectively.

E. Training methods

Each input image has a corresponding reference image as a training target during the training process. At the same time, each image will have a one-to-one corresponding reference image as the image enhancement process. The mean square error based on the pixel value, as shown in Equation (4), is adopted as the loss function to calculate the difference between the enhanced image and the target image.

$$L=\frac{1}{H\times W\times C}\sum_{x,y,z=1}^{H,W,C}(\hat{D}(I)_{x,y,z}-R(I)_{x,y,z})^2 \quad (4)$$

Where H represents the height of the image, W represents the width of the image, and C represents the number of channels in the image; x, y, and z are the coordinates of the three dimensions of the image, respectively; $\hat{D}(I)$ represents the output image in this paper; $R(I)$ represents the target image dataset. In addition, this paper uses the Adam optimizer [6] to optimize the parameters of the sacred network.

IV. TRAINING METHODS

The correctness of the method is proved by the computer simulation and comparison test of PG500-216 (V100-32GB). This paper takes advantage of the deep learning architecture of PyTorch to conduct an in-depth study of this method. In deep learning training, the batch size used is 2, and the learning efficiency is 0.001 after more than 3000 times. Moreover, this paper conducted experiments on blurred and cleaned images to verify this algorithm's universality.

The batches size used in the deep learning training is 2, the learning rate is 0.001, and more than 3000 rounds of training are performed according to the two types of image blur and clear.

The processed images captured by the original underwater robot are derived from many authentic underwater images in the UIEB dataset [4], which are all captured in natural underwater scenes, with a total of 890 original authentic images. This paper uses all the images for training. It then uses the image recognition algorithm to select 50 relatively clear and blurred images for testing to verify the universality of the image enhancement algorithm in this paper. Moreover, the algorithm of this paper is compared with five algorithms such as CLAHE[5], HE[6], ICM[7], RGHS[8], and UCM[9] from the two aspects of blurred and clear images. It mainly compares and analyzes the differences between the six methods in three parts: visual effect, quality index, and operation speed in processing the same batch of images.

A. Training method

In this experiment, the UIEB dataset was classified into 100 pieces with low turbidity and 100 pieces with high turbidity. Then, image enhancement was performed using CLAHE[5], HE[6], ICM[7], RGHS[8], and UCM[9], as well as the algorithms in this paper. Their results are compared with the input images. Fig. 6. shows the comparison results of the data sets with lower turbidity, and Fig. 7. shows the comparison results of the datasets with higher turbidity.

The first column in the figure is the unprocessed underwater image selected from the UIEB dataset [4]. The algorithm effect after image enhancement is detailed in the last six columns. From the visual effect of image enhancement, the overall visual effect of underwater image enhancement of this algorithm is more significant, and the contrast and detail clarity is significantly improved. After processing this algorithm, the blue and green underwater images can be effectively eliminated. However, some images processed by HE[6] and UCM[9] algorithms generally show a red light phenomenon. The images processed by the CLAHE[5], HE[6], ICM[7], and RGHS[8] algorithms have problems such as high color saturation, unclear image, low contrast, and dark background color.

Fig. 6. Low turbidity image enhancement of real underwater images with ICM, RGHS, UCM, CLAHE, HE, Ours.

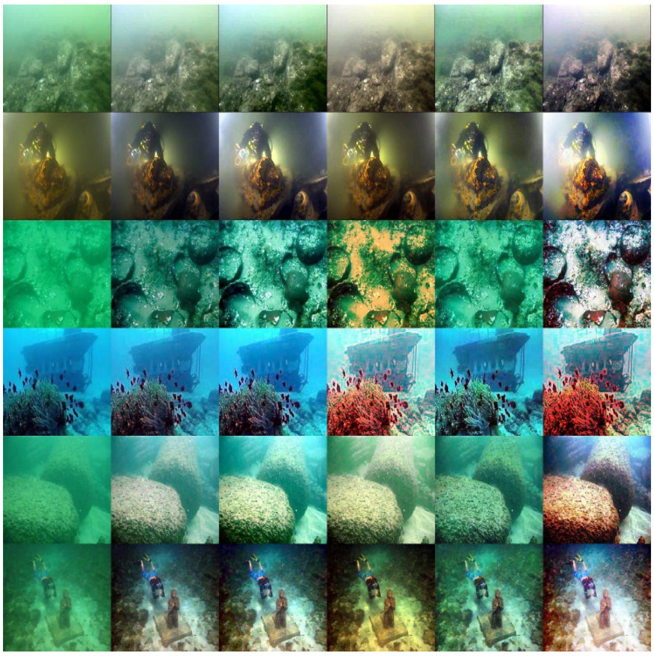

Fig. 7. High turbidity image enhancement of real underwater images with ICM, RGHS, UCM, CLAHE, HE, Ours.

B. Analysis of quality indicators

This paper selects six categories of reference indicators with and without reference indicators to evaluate the image quality of underwater images enhanced by different algorithms. Four reference indicators are obtained by comparing the enhanced image with the actual image and calculating the similarity, namely, Structural Similarity (SSIM). Furthermore, nevaluate indicators, the Underwater Image Quality Assessment (UIQM) obtained after integrating a single image.

Table I shows the comparison of the experimental results between the algorithm in this paper and the CLAHE[5], HE[6], ICM[7], RGHS[8], and UCM[9] algorithms. In terms of processing low turbidity images, the algorithm in this paper performs better in SSIM and UIQM than the five algorithms in the comparative analysis. Larger SSIM and UIQM values mean that the processed image has less distortion and higher color contrast and clarity. Thus, the effectiveness of the proposed algorithm in underwater image enhancement and the reliability of the enhanced image quality is verified.

TABLE I. IMAGES OF LOW TURBIDITY

Algorithm	Evaluate	Nevaluate
	SSIM	UIQM
CLAHE	0.810	0.917
HE	0.772	1.198
ICM	0.791	0.511
RGHS	0.820	0.764
UCM	0.787	0.823
Ours	**0.843**	**0.904**

Table II shows that the algorithm in this paper and the CLAHE[5], HE[6], ICM[7], RGHS[8], and UCM[9] algorithms are dealing with high turbidity images, and the quality indicators have different degrees when dealing with blurry images. A slight decrease, slightly worse than the HE[6] algorithm and RGHS[8] algorithm. However, compared with the CLAHE[5] and RGHS [8] algorithms, the algorithm in this paper significantly affects UIQM and SSIM in dealing with high turbidity images and has obvious advantages. Compared with other algorithms such as HE [6] and ICM [7], they are comparable.

TABLE II. IMAGES OF HIGH TURBIDITY

Algorithm	Evaluate	Nevaluate
	SSIM	UIQM
CLAHE	0.233	0.539
HE	0.177	0.900
ICM	0.256	0.263
RGHS	0.213	0.553
UCM	0.268	0.658
Ours	**0.376**	**0.596**

Although the algorithm in this paper is slightly inferior to the HE[6] algorithm and the RGHS[8] algorithm in the UCIPE index in dealing with precise and blurred images, the main reason is that the traditional method performs post-processing on the enhanced picture to enhance the color of the processed image. This step makes the enhanced image perform better in the index value, but it will bring about the problem that the image's color saturation is too high, and the image is not clear. The processed image faces image distortion issues, such as too dark color, low contrast, and dark background color. Therefore, the algorithm in this paper has achieved significant advantages in analyzing some quality indicators, and the performance is much more effective.

C. Operation Speed Analysis

This paper paid particular attention to the feasibility and real-time performance of the algorithm applied to the actual scene when performing real-time underwater image enhancement. After ensuring the enhanced image's quality, the algorithm's running speed is also an essential indicator. Table III compares the time spent by the algorithm in this paper and the six methods of CLAHE[5], HE[6], ICM[7], RGHS[8], and UCM[9] to process ten identical images in seconds (s). The less time it takes to process the same number of images, the faster the algorithm's operation speed. The algorithm in this paper has a significant advantage over other algorithms in terms of operation speed. The main reason is that the algorithm in this paper simplifies the underwater imaging model into two modules: background light estimation and transmission map estimation. The convolutional neural network uses a smaller convolution kernel. At the same time, the innovative introduction of the algorithm's attention algorithm in this paper significantly improves the efficiency of image processing.

TABLE III. SPEED OF DIFFERENT ALGORITHMS

Algorithm	Calculating Speed
CLAHE	0.06900s
HE	0.03124s
ICM	6.16206s
RGHS	8.24277s
UCM	14.47053s
Ours	**0.00068s**

V. CONCLUSION

This paper improves the foggy image and applies it to deep learning and imaging models for underwater images. Instead of background scattering and direct estimation, methods such as dilated convolution, multi-scale convolution kernels, and attention enhancement are adopted. Through a series of simulation experiments, it has been proved that the proposed method can quickly and accurately reflect the color and details of underwater images. Compared with the existing ICM, RGHS, UCM, CLAHE, HE, and other methods, it has been proved that the method has the advantages of speed and can adapt well to the real-time needs of domestic underwater robots. In addition, the method can also be applied to other computer vision fields. The method has a particular application value in underwater image restoration, image segmentation, target detection, etc.

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