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Sea Cucumber Image Dehazing Method by Fusion of Retinex and Dark Channel

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Abstract: This paper proposes a method based on the prior fusion of Retinex and dark channel to enhance the defogging of underwater sea cucumber images. Firstly, the original RGB image is pre-processed by dark channel prior, and then the reflection property of the image is preserved by weighted average of pixels in the image. Then, the original image is convolved with a Gaussian template to generate a high-frequency enhanced image. Finally, the brightness and saturation of the image are enhanced by changing the values of S and V in the HSV image. The experimental results are represented by four evaluation indicators such as the MSE. By processing images of sea cucumber, we obtained MSE, ENL, EI, and SNR values of 1.9782, 14.4049, 6.9586, and 14.9172, respectively. Compared with other methods, the image processed by our method has better performance in evaluating indicators. It shows that our method shows great performance in the defogging and enhancement of underwater sea cucumber images.

***Keywords**:* Dark channel; Retinex; HSV; Image dehazing; Image enhancement

1. INTRODUCTION

Sea cucumber products contain rich protein and vitamins, and have the characteristics of low fat and good balance of nutrition, and become an important source for people to consume high quality animal protein **(Hu et.al,2015)**. The shape, size, color and texture of sea cucumbers play an important role in sea cucumber breeding. It can not only reflect the basic growth of sea cucumber, but also provide reference for the feeding, fishing and grading of sea cucumber, and provide data support for the monitoring of breeding environment **(Zhu et.al,2008)**. At present, the use of computer vision technology to estimate biomass has become a research hotspot[ ]. It not only effectively reduces human and material resources, but also quickly and accurately obtain various statistical information of sea cucumber, providing a basis for efficient and economical breeding of sea cucumber.

Due to the scattering, absorption effect of the light and the interference of underwater suspended matter, the collected images of the sea cucumber have serious fogging and color distortion, which restricts the development of the underwater optical vision technology. Therefore, the underwater sea cucumber images need to be enhanced to enhance the visual quality. Traditional methods have contrast enhancement techniques **(Wang et.al,1999)**, histogram equalization **(Chen et.al,2012)**, etc. However, these methods often lead to excessive image enhancement and whitening.

In this paper, a comprehensive method based on the transcendental fusion of Retinex and dark channel is proposed, which combines HSV space color enhancement theory to avoid color distortion while maintaining the freshness of the image. The experimental results show that this method is simple and can solve the problem of pseudo shadow phenomenon and color distortion, noise amplification and so on, without prior knowledge, it can obtain a better quality color image.

2. RELEATED WORK

In recent years, research based on image enhancement has focused on the performance of underwater image quality degradation and selected corresponding image enhancement techniques, such as histogram equalization **(Yang et.al,2016)**, Low-pass filter **(Srividhya et.al,2015)**, and wavelet transform **(Singh et.al,2015)**.

Hitam **(Hitam et al., 2013)** proposed a hybrid contrast-constrained histogram equalization method for underwater image enhancement. Aiming at the problem that the quality of underwater image is greatly affected by illumination and turbidity, Qiao Xi **(Qiao et al., 2017)** adopts the method of constrained contrast adaptive histogram equalization and wavelet transform to enhance the image. The underwater image noise will increase due to non-uniform illumination, microbes, etc. Emberton **(Emberton et al., 2015)** The image layering method is used to estimate the atmospheric light, which avoids the oversaturation phenomenon of the restored image, but is easily affected by the image noise and uneven light conditions. These image enhancement methods have achieved certain effects, because of the lack of consideration of the underlying causes of underwater image degradation, the enhanced results often fail to accurately reflect the actual appearance of the images.

For this purpose, by analyzing the imaging mechanism of underwater images, Roser **(Roser et al., 2014)** established an underwater imaging model for enhancing image sharpness under natural light and turbid conditions. Seemakurthy **(Seemakurthy et.al, 2015)** proposes a mathematical model for the motion blurred image captured by light refraction due to the refraction of light. The unidirectional cyclic wave is regarded as a spatial invariant for underwater blurred image

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recovery. The single method is not ideal for the treatment of underwater images. Image fusion is gradually applied to underwater image enhancement **(Ancuti et al., 2012)**. Color compensation, histogram equalization and other enhancement techniques can be used to process underwater images. Celebi **(Celebi et.al, 2012)** proposed the use of empirical mode decomposition for underwater image enhancement processing, through the original image signal is decomposed into a series of intrinsic mode function, then use genetic algorithm to calculate each modal function to get the weights of spectral channels component, to improve the image visual quality, the method than the traditional contrast stretching and histogram equalization can get better results.

With the development of deep learning techniques, ****, such as Yang **(Yang et al., 2017)** proposed a joint optimization based on image content and texture constraint of multi-scale neural plaques synthetic method to achieve the latest repair precision. Then because of the underwater acquisition image atomization phenomenon is more serious, so the method based on deep learning remains to be breakthrough.

Since the zooplankton in the aquaculture water in the offshore area has increased the difficulty of image defogging and enhancement, we proposed a method based on the prior fusion of Retinex and dark channel for image enhancement and recovery of underwater sea cucumber based on the characteristics of near-seawater breeding water quality. It has improved the quality of underwater sea cucumber images.

The contributions of this paper are:(1) Increase the exposure between the Retinex and dark channel prior methods to increase the brightness of the pre-processed image. (2) Set the range of defogging coefficient ω according to the color characteristics of sea cucumber. (3) Combining HSV spatial color theory to enhance sea cucumber image saturation.

3.IMAGE ENHANCEMENT MODEL

3.1 Dark channel prior algorithm

The de-fog algorithm based on the dark channel prior is a statistical algorithm. In most regions, some pixels always have at least one color channel with a very low value. That is, the minimum value of the light intensity in this area is a very small number. For any input image J, the dark channel can be expressed by the following expression:

$$J^{dark}(x) = \min_{y\in\Omega(x)}\left(\min_{c\in\{r,g,b\}} J^{c}(y)\right) \tag{1}$$

Where J^c denotes each channel of a color image, and $\Omega(x)$ denotes a window centered on pixel x. First calculate the minimum value of the RGB component of each pixel, store it in a grayscale image with the same size as the original image, and then perform the minimum filtering on this grayscale image. The filter radius is determined by the size of the window. The theory of dark channel priors indicates:

$$J^{dark} \to 0. \tag{2}$$

There are three main factors that result in low channel values in dark primary colors: a) projection of natural scenery; b) colorful objects or surfaces in some of the three channels of RGB have very low values; c) darker colors Object or surface. There are shadows or colors everywhere in the images of underwater sea cucumbers.

The fog map formation model normally described by the following equation:

$$I(x) = J(x)t(x) + A(1-t(x)) \tag{3}$$

Where $I(x)$ is the image to be defogged, $J(x)$ is the fog-free image we want to recover, A is the global atmospheric light component, and $t(x)$ is the transmittance. The current known condition is $I(x)$, which requires the target value $J(x)$. Through the above formula, our goal is to calculate the original fog-free image, the transmittance, and the estimated global atmospheric light composition from the existing photographs.

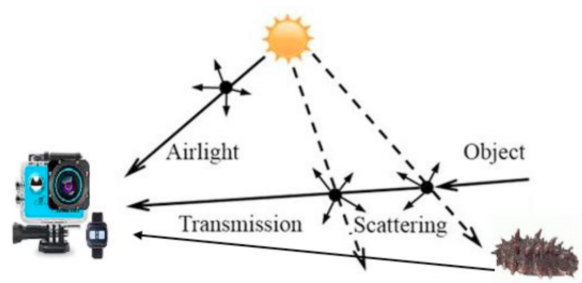


Fig. 1. Underwater sea cucumber image fog principle

Fig.1 This image describes the principle of sea cucumber imaging, which is an image transmitted directly and partially scattered, and a final image formed by mixing with global atmospheric light components, that is $I(x)$.

For the calculation of the transmittance, there is an existing formula that indicates that when the material in the atmosphere is homogeneous, the transmittance t can be expressed as:

$$t(x) = ex^{-\beta d(x)} \tag{4}$$

Where β is the parameter for atmospheric scattering and d is the depth of field. This formula expresses that scene radiance exhibits exponential attenuation with increasing distance. Because if we get this transmittance, we can get the depth of the scene according to this law.

The basic flow of the defogging algorithm based on the dark channel prior is as follows:

(1) The transmittance is obtained. According to formula (3), the equation can be divided by both sides and then converted.

$$\tilde{t}(x) = 1 - \omega \min_{y\in\Omega(x)}\left(\min_{c}\left(\frac{I^{c}(y)}{A^{c}}\right)\right) \tag{5}$$

In fact, $\min_{y\in\Omega(x)}\left(\min_{c}\left(\frac{I^c(y)}{A^c}\right)\right)$ is the dark channel of the regularized image $\frac{I^c(y)}{A^c}$. Considering the existence of the atmospheric perspective phenomenon, if the fog of the image is completely removed, it will look unnatural and may lose the depth information. Therefore, it is necessary to keep a small amount of fog on the distant objects, so it is introduced in the formula. The parameter ω, we set value is 0.90.

(2) Get a restored image. When the value of the projective graph t is small, the value of J will be too large, so that the whole image will be over-whitened. Therefore, We set a threshold T_0. When the value of t is less than T_0, let $t = T_0$. Therefore, the final recovery formula is as follows:

$$J(x) = \frac{I(x) - A}{\max\left(t(x), T_0\right)} + A \tag{6}$$

(3)About the setting of ω. Parameter ω is an adjustment parameter. When this parameter is 0, it means that the fog is not removed. If the parameter is 1, it means that all the fog is removed.

3.2 Improved dark channel prior algorithm

The priori of dark colors is a focal result and is the result of a large number of outdoor fog-free photos. If the target scene is intrinsically similar to atmospheric, such as snow, white walls, and the sea, the prerequisites are Not. Correctly, it can't obtain fairly results. Therefore, we use the Retinex and dark channel prior fusion, combined with HSV theory to enhance the effect of image defogging. The basic steps of the improved dark channel prior algorithm are as follows.

(1) Logarithmically separates the irradiated light component $L(x,y)$ and the reflected light component $R(x,y)$.

$$\log J(x,y) = \log R(x,y) + \log L(x,y) \tag{7}$$

(2) The reflection image is hypothetically estimated as a spatially smooth image, and the original image is convoluted with a Gaussian template to obtain a low-pass filtered image $D(x,y)$, $F(x,y)$ denotes a Gaussian filter function.

$$D(x,y) = \log \mathrm{S}(x,y) * F(x,y) \tag{8}$$

(3) In the logarithmic domain, the low-pass filtered image is subtracted from the original image to obtain a high-frequency enhanced image $G(x,y)$.

$$G(x,y) = \log \mathrm{S}(x,y) - \log D(x,y) \tag{9}$$

(4) Opposite $G(x,y)$ to get an enhanced image $R(x,y)$.

$$R(x,y) = \exp G(x,y) \tag{10}$$

(5) Enhanced based on HSV theory.

$$R_{HSV}(x,y) = G\left\{\sum_{n=1}^{N}\omega_n\left[\log\left(I_s(x,y) - \log\left(F_n(x,y) * I_s(x,y)\right)\right)\right]\right\} \tag{11}$$

Where N is the number of scales. $I_s(x,y)$ is the image after the RGB image is converted to the HSV. ω_n is the weight corresponding to the dimension n and $\sum_{n=1}^{N}\omega_n = 1$; G represents the gain coefficient, which is taken as 1 in the experiment.

4. EXPERIMENT AND ANALYSIS

4.1 Simulations

Simulations were performed on MatLab R2017a to verify the enhancement of the underwater sea cucumber image using the Retinex and dark channel prior fusion method. First, the gray scale image of the underwater sea cucumber was selected as the object of the simulation and the dark channel prior fusion was performed. Retinex processing and gradation transformation for image enhancement processing, select a few typical images in the experiment (if there is a single sea cucumber, more than sea cucumber, with or without attachment base, etc.), the effect of the comparison chart shown in Fig. 3 to Fig. 5.

From Fig. 3 to Fig. 5, we can see that among the seven methods used in the experiment, our method gets the best effect, and the multi-scale Retinex method is better, while the other four methods are obviously worse from the visual sense. It is based on the human subject's subjective visual system to establish a mathematical model, and through specific formulas to calculate the quality of the image. In this paper, the mean square error (MSE), equivalent coefficient (NEL), information entropy (IE), and signal-to-noise ratio (SNR) are calculated between the processed image and the original image. Evaluation indicators to compare effectiveness. The MSE reflect the mathematical statistical differences between the reconstructed image and the original image.

4.2 Evaluation System

(1) Mean Square Error (MSE). MSE represents the mean square error of the current image X and the reference image Y, and H, W are the height and width of the image, respectively. In general, the smaller the MSE after image processing, the better the processing effect.

Table 1 Quantitative results in terms of MSE, ENL,IE and SNR for images in Figs.3-Figs.5

Approach	MSE	ENL	EI	SNR
Our method[]	1.9782	14.4049	6.9586	-14.9172
Gaussian	9.8848	43.1130	6.8400	-9.0768
Dark Channel Prior	6.1116	45.9172	6.2426	-11.6342
Adaptive Histogram Equalization	3.5370	58.3764	5.8557	-3.4035
Adaptive color scale and contrast	30.4686	71.0088	6.8741	-6.4212
Histogram equalization	34.4957	3.0148	6.6461	-16.6520
Multiscale Retinex	2.2544	27.1569	6.4470	-14.2921

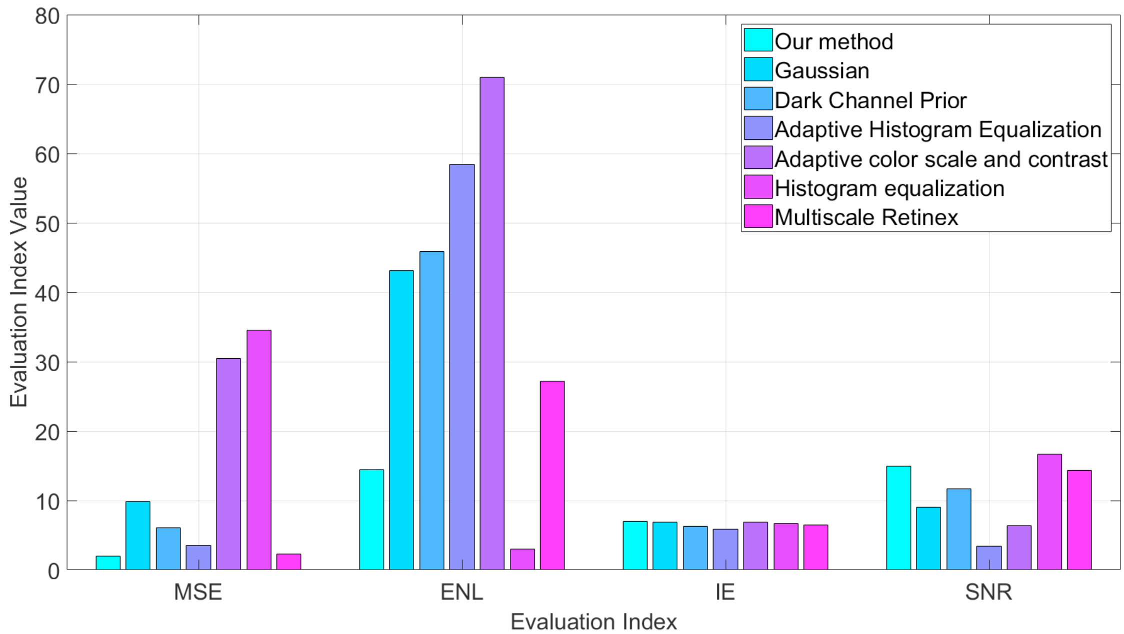
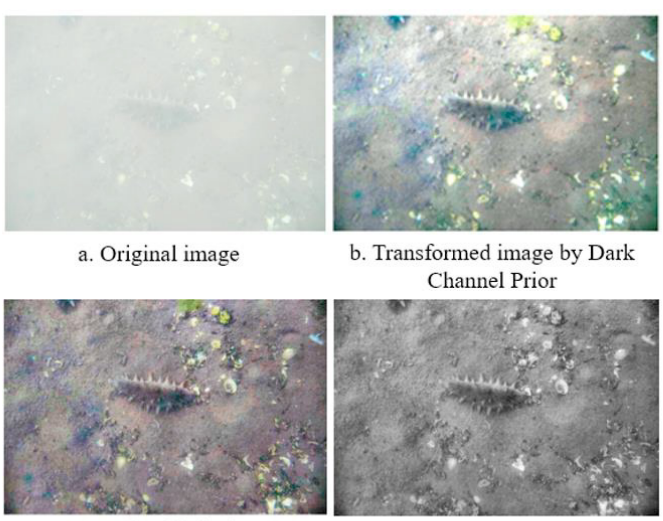


Figure 2 Evaluation Index Histogram



a. Original image

b. Transformed image by Dark Channel Prior

c. Our Method

d. Transformed image by Linear conversion

Fig. 3. Single sea cucumber image enhancement process diagram

$$MSE=\frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W}\left(X\left(i,j\right)-Y\left(i,j\right)\right)^{2} \quad (12)$$

Where i and j respectively represent the horizontal and vertical coordinates of the image pixels.

(2) Equivalent numbers of looks(ENL). This is an indicator of the smoothness of the uniform area. In general, we can select several regions of interest to find the equivalent coefficients and then average them, or directly determine the equivalent visual number of the image.

$$ENL=\left(\frac{1}{H}\right)\sum_{h=1}^{H}\frac{\mu_h^2}{\sigma_h^2} \quad (13)$$

Where H denotes the number of selected regions, μ denotes the average of selected region pixels, and σ denotes the mean squared error of the selected region

(3) Information Entropy(IE). Entropy is a measure of the diversity or uniformity of microscopic states in thermodynamics and represents the disorder of the system. Assume that a system X may be in a different centralized state $x_1,x_2,\cdots,x_n,p\left(x\right)$ represents the probability of occurrence of a state $x_i\left(i=1,2,\cdots,n\right)$, then the information entropy $H\left(x\right)$ of the system is defined as follows.

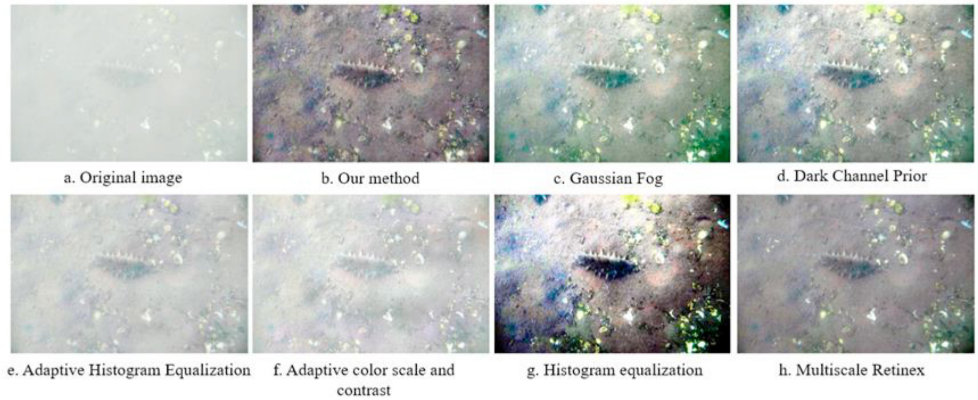


Fig. 4. Different methods for image processing of single sea cucumber

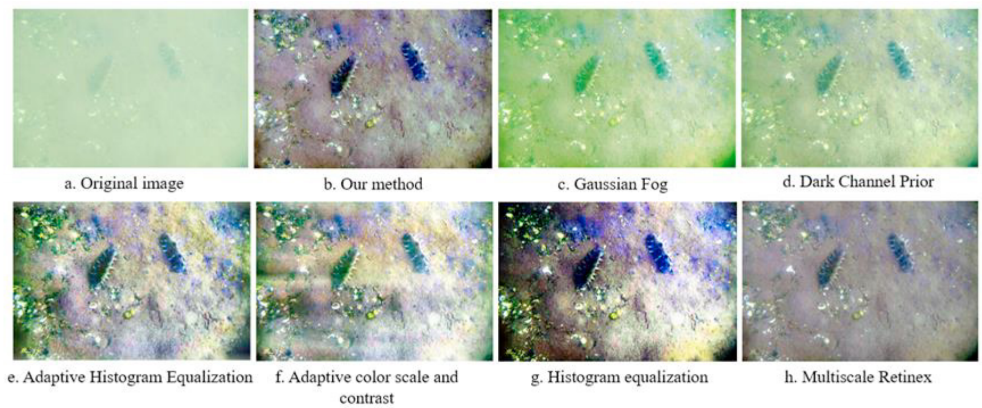


Fig. 5. Different methods for image processing of multiple sea cucumbers

$$H(x) = -\sum_{i=1}^{n} p(x)\log\left(p(x)\right) \tag{14}$$

Where $0 \le p(x) \le 1$ and $\sum_{i=1}^{n} p(x)=1$. The greater the information entropy, the higher the disorder of the information and the greater the amount of information contained.

(4) Signal to Noise Ratio (SNR). If we regard $f(x,y)$ as the sum of the original graph $g(x,y)$ and the noise image $e(x,y)$, the mean square noise of the output graph is as follows.

$$\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)^2 \Big/ \sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(f(x,y)-g(x,y)\right)^2 \tag{15}$$

The Table 1 shows that the above five images in Fig. 3 to Fig. 5 are based on Retinex and dark channel prior fusion processing, combined with HSV enhancement theory transformed MSE values, ENL values, IE values and SNR values. The results show that our fusion algorithm has better performance in image defogging enhancement.

The collected sea cucumber images were processed, and the values of MSE, ENL, EI and SNR in Table 1 were obtained. From the table, we can observe that the image MSE based on the prior fusion method of Retinex and the dark channel has the best effect value, ENL, information entropy, SNR effect value is good, which is among 4 indicators. According to the analysis data in the table, the method based on the prior fusion of the Retinex and the dark channel has a better effect on the enhancement of underwater sea cucumber images. As shown in Fig.2, the result of each evaluation index is visually displayed as a bar graph. Since the value of the SNR indicator is negative, the value of the SNR is represented as a reciprocal number.

5. CONCLUSIONS

This article takes the underwater sea cucumber image as the research object, aiming at the phenomenon of blurred image. Based on the prior fusion method of Retinex and dark channel, combined with the theory of HSV spatial color enhancement, the phenomenon of color distortion is avoided while maintaining the vividness of the image. The experimental results show that this method is simple and can solve problems such as color distortion and serious fogging, and can obtain better quality color images without prior knowledge. By evaluating the four methods of comparison and fusion of the function MSE, ENL, IE and SNR, we can know that our algorithm shows better performance in the defogging and enhancement of underwater sea cucumber images. However, the disadvantage of this method is the increased processing time. In the subsequent experiments, the model will continue to be optimized and the time efficiency will be improved.

6. ACKNOWLEDGEMENTS

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REFERENCES

A. T. Çelebi, & S. Ertürk. (2012). Visual enhancement of underwater images using Empirical Mode Decomposition and wavelet denoising. *Signal Processing and Communications Applications Conference*,39,1-4.

Bekaert, P., Haber, T., Ancuti, C. O., & Ancuti, C. (2012). Enhancing underwater images and videos by fusion. *Computer Vision and Pattern Recognition*,6428,81-88.

Chen, S. D. (2012). A new image quality measure for assessment of histogram equalization-based contrast enhancement techniques. *Digital Signal Processing*, 22(4), 640-647.

Emberton, S., Chittka, L., & Cavallaro, A. (2015). Hierarchical rank-based veiling light estimation for underwater dehazing. *British Machine Vision Conference*,125,1-12.

Hitam, M. S., Awalludin, E. A., Wan, N. J. H. W. Y., & Bachok, Z. (2013). Mixture contrast limited adaptive histogram equalization for underwater image enhancement. *International Conference on Computer Applications Technology*, 1-5.

Hu, J., Wang, J., Zhang, X., Fu, Z., & University, C. A. (2015). Research status and development trends of information technologies in aquacultures. *Transactions of the Chinese Society for Agricultural Machinery*, 46(7), 251-263.

Li, J., Skinner, K. A., Eustice, R. M., & Johnson-Roberson, M. (2018). Watergan: unsupervised generative network to enable real-time color correction of monocular underwater images. *IEEE Robotics and Automation Letters*, 3(1),387-394.

Qiao, X., Bao, J., Zeng, L., Zou, J., & Li, D. (2017). An automatic active contour method for sea cucumber segmentation in natural underwater environments. *Computers & Electronics in Agriculture*, 135(C), 134-142.

Roser, M., Dunbabin, M., & Geiger, A. (2014). Simultaneous underwater visibility assessment, enhancement and improved stereo. *IEEE International Conference on Robotics and Automation*, 3840-3847.

Seemakurthy, K., & Rajagopalan, A. N. (2015). Deskewing of underwater images. *IEEE Trans Image Process*, 24(3), 1046.

Singh, G., Jaggi, N., Vasamsetti, S., Sardana, H. K., Kumar, S., & Mittal, N. (2015). Underwater image/video enhancement using wavelet based color correction (WBCC) method. *Underwater Technology*, 1-5.

Srividhya, K., & Ramya, M. M. (2015). Performance analysis of pre-processing filters for underwater images. *International Conference on Robotics, Automation, Control and Embedded Systems*, 1-7.

Wang, Y., Chen, Q., & Zhang, B. (1999). Image enhancement based on equal area dualistic sub-image histogram equalization method. IEEE Transactions on Consumer Electronics, 45(1), 68-75.

Yang, C., Lu, X., Lin, Z., Shechtman, E., Wang, O., & Li, H. (2016). High-resolution image inpainting using multi-scale neural patch synthesis.

Yang, W., Xu, Y., Qiao, X., Rao, W., Li, D., & Li, Z. (2016). Method for image intensification of underwater sea cucumber based on contrast-limited adaptive histogram equalization. *Transactions of the Chinese Society of Agricultural Engineering,* 32(6):197-203.

Zhu, C. R. (2008). Application of computer vision technology in aquaculture. *Journal of Zhejiang Ocean University,* 27(4),439-443.