Received January 22, 2019, accepted February 1, 2019, date of current version April 15, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2897691

Low-Light Underwater Image Enhancement for Deep-Sea Tripod

YUJIE LI[1], JIANRU LI[2], YUN LI[1], HYOUNGSEOP KIM[3], AND SEIICHI SERIKAWA[3]

[1]School of Information Engineering, Yangzhou University, Yangzhou 225127, China
[2]State Key Laboratory on Marine Geology, Tongji University, Shanghai 200092, China
[3]School of Engineering, Kyushu Institute of Technology, Kitakyushu 8048550, Japan

Corresponding authors: Yujie Li (yzyjli@gmail.com) and Jianru Li (lijianru@tongji.edu.cn)

This work was supported in part by the Leading Initiative for Excellent Young Researcher (LEADER) of the Ministry of Education, Culture, Sports, Science and Technology-Japan under Grant 16809746, in part by the Grants-in-Aid for Scientific Research of the Japan Society for the Promotion of Science under Grant 17K14694, in part by the Research Fund of the State Key Laboratory of Marine Geology, Tongji University, under Grant MGK1608, in part by the Research Fund of the Telecommunications Advancement Foundation, in part by the Open Collaborative Research Program, National Institute of Informatics Japan (NII), in part by the Japan-China Scientific Cooperation Program under Grant 6171101454, in part by the International Exchange Program of the National Institute of Information and Communications (NICT), and in part by the Fundamental Research Developing Association for Shipbuilding and Offshore.

ABSTRACT To monitor the sedimentary process and morphological evolution in the South China Sea, free-ascending deep-sea tripod (FDT) has been developed. This FDT was equipped with a deep-sea camera and landed on the sea floor at a depth of 2100 m. Although the FDT was equipped with an artificial light, the battery capacity limited the duration and intensity of light. Therefore, enhancing such low-illumination images to obtain clear visual effects is an important advancement for analyzing the geological evolution process. In this paper, an adaptive bright-color channel-based low-light underwater image-enhancement method and a denoising method are proposed to enhance such images and remove noise and artifacts. The experimental results demonstrated that the proposed method outperformed state-of-the-art methods.

INDEX TERMS Image enhancement, underwater imaging, low lighting, deep-sea.

I. INTRODUCTION

Underwater imaging is becoming more and more important due to the limitations of land resources. The underwater optical camera, one of the most important sensors for capturing information from the ocean, is the subject of ongoing development by many researchers [1]. Most underwater cameras simply cover traditional land-based cameras with a housing base. The captured underwater images suffer from low contrast, color distortions, and heavy noise. Because light is attenuated through water, the energy of light is absorbed by water, and therefore, the captured images appear as color distortions. Forward and backward scattering results in low contrast. Meanwhile, sediments in water also degrade the resulting image.

There are many underwater image enhancement methods for improving the quality of the visual effectiveness of the captured image. Chiang and Chen [2] proposed a wavelength compensation and dark channel prior-based dehazing method for enhancing an underwater image. This research was the first use of the wavelength compensation in a dark channel prior dehazing model, and the processed images performed well. However, this method used a single wavelength in computing, which readily causes color distortions. Fattal [3] used a color-lines method to estimate the veiling light and remove the haze-like objects in the images. However, for heavy turbidity images, it is difficult to remove the scatters. Lu *et al*. [4] proposed an improved veiling light estimation method, to first remove the high light of the images and then to calculate the attenuation coefficients to achieve better results. However, this method is time-consuming and not suitable for applications in underwater robots. Meanwhile, most recent works focus on using deep learning or big data methods to solve the issues of underwater images [5]–[8]. However, these methods ignore many fatal problems in practice, and all recent models have limitations. One is that when using a generate adversarial network to produce the underwater images, we do not even know the actual underwater imaging model. Another is that the attenuations in water are affected by seasonal, geographical, and climate variations. It is difficult to use a simple dataset or a simple approximate model to produce an estimate.

The associate editor coordinating the review of this manuscript and approving it for publication was Huimin Lu.

Unfortunately, existing single underwater image enhancement methods only focus on the proposal of new optical imaging models or enhancement models to recover the color or remove the scatter from the image [15]–[22]. Additionally, they are nearly all focused on practical problems such as low lighting in real underwater monitoring systems.

In this paper, we propose a method to improve the image brightness in low lighting, remove the heavy noise, and use just one single image as input. The remainder of this paper is organized as follows. Section 2 introduces some related works and points out the advantages and weaknesses of recent work. In Section 3, we propose an architecture of low light underwater image enhancement that is based on the bright color channel model and denoising method. Experimental results and discussions are presented in Section 4. Finally, we conclude this paper in Section 5.

II. RELATED WORK

To the best of our knowledge, there are no researchers focused on the research of low-light underwater image enhancement.

A. DARK CHANNEL MODEL

Marques *et al.* [9] was the first person in the world to use the image processing method to recover low-light images. This method was based on Dark Channel Prior and used guided filtering to smooth the transmission map. It used the traditional air-based mathematic image acquirement model

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

where I is the observed intensity hazy image, J is the scene radiance haze-free image, A is the atmospheric light, and t is the medium transmission–the light that reaches the camera without scattering. The minimal pixel channel of the image is describe as

$$J^{dark}(x) = min_{y\in\Omega(x)}\left(min_{c\in\Omega(r,g,b)} J^{c}(y)\right) \tag{2}$$

In the hypothesis of dark channel prior, the minimal pixel channel will tend to 0. Atmospheric light A is calculated by initially choosing the 0.1% brightest pixels of the image. In the dark channel prior, the medium transmission is calculated by

$$t(x) = 1 - \omega \min_{y\in\Omega(x)}\left(min_c \frac{I^c(y)}{A^c}\right) \tag{3}$$

where ω is the constant between 0 and 1. After the estimation of medium transmission, the haze-less image can be obtained by

$$J(x) = \frac{I(x) - A}{\max(t(x), t0)} + A \tag{4}$$

where t0 is the constant to avoid the lower value of this denominator. Then, the authors used the fast guided filter to refine the medium transmission map.

Some additional methods are considered below.

B. HISTOGRAM EQUALIZATION ALGORITHM

When the image pixels are evenly distributed, the image contrast is high. Histogram equalization utilizes this image characteristic to map the original image so that the image pixels are evenly distributed, thereby achieving the purpose of improving image contrast.

The function expression [11] for the histogram equalization of the image is:

$$s_k = T(r_k) = (L-1)\sum_{j=0}^{k} Pr(r_j) = \frac{L-1}{MN}\sum_{j=0}^{k} n_j, \quad k = 0,1,2,\ldots,L-1 \tag{5}$$

where MN is the total pixel of the image, n_k is the number of pixels with greyscale r_k, and L is the number of possible grey levels in the image.

$$p_r(r_k) = \frac{n_k}{MN} \tag{6}$$

Eq. (6) is the probability that the grey level r_k appears in a digital image.

The histogram transformation technique makes the histogram of the target image meet the requirements by selecting the transformation function $T(r)$. However, the histogram equalization algorithm often causes grey level merging after image enhancement, and there are problems such as local over-enhancement and loss of detailed information.

C. RETINEX ALGORITHM

Color constancy image enhancement technology is an enhancement method based on the visual effects of images. The Retinex algorithm [10] proposed by Land *et al.* is the most influential color constant vision calculation theory.

The Retinex algorithm considers the perceptual image to be composed of the product of luminance information and reflection information. The formula is as follows:

$$\mathrm{I}(x, y) = L(x, y) \cdot R(x, y) \tag{7}$$

In Eq. (7), $I(x, y)$ represents the image observed by the human eye; $L(x, y)$ represents the luminance component of the image, which determines the dynamic range of an image; and $R(x, y)$ represents the reflection component, which carries the details of the image.

In practical applications, we are more concerned with how to remove the luminance component to get the reflection image we ultimately need. The single-scale Retinex algorithm uses the center/surround method [12] to estimate the luminance component $L(x, y)$. The mathematical expression is as follows:

$$L(x, y) = I(x, y) * F(x, y) \tag{8}$$

In the above formula, $*$ denotes a convolution operation, and $F(x, y)$ is the center surround function. The mathematical expression of $F(x, y)$ is:

$$F(x, y) = \kappa \cdot exp\left[\frac{-\left(x^2 + y^2\right)}{\sigma^2}\right] \tag{9}$$

In the above equation, σ is the Gaussian surround scale and κ is between 80–100. k is a normalized molecule, satisfying

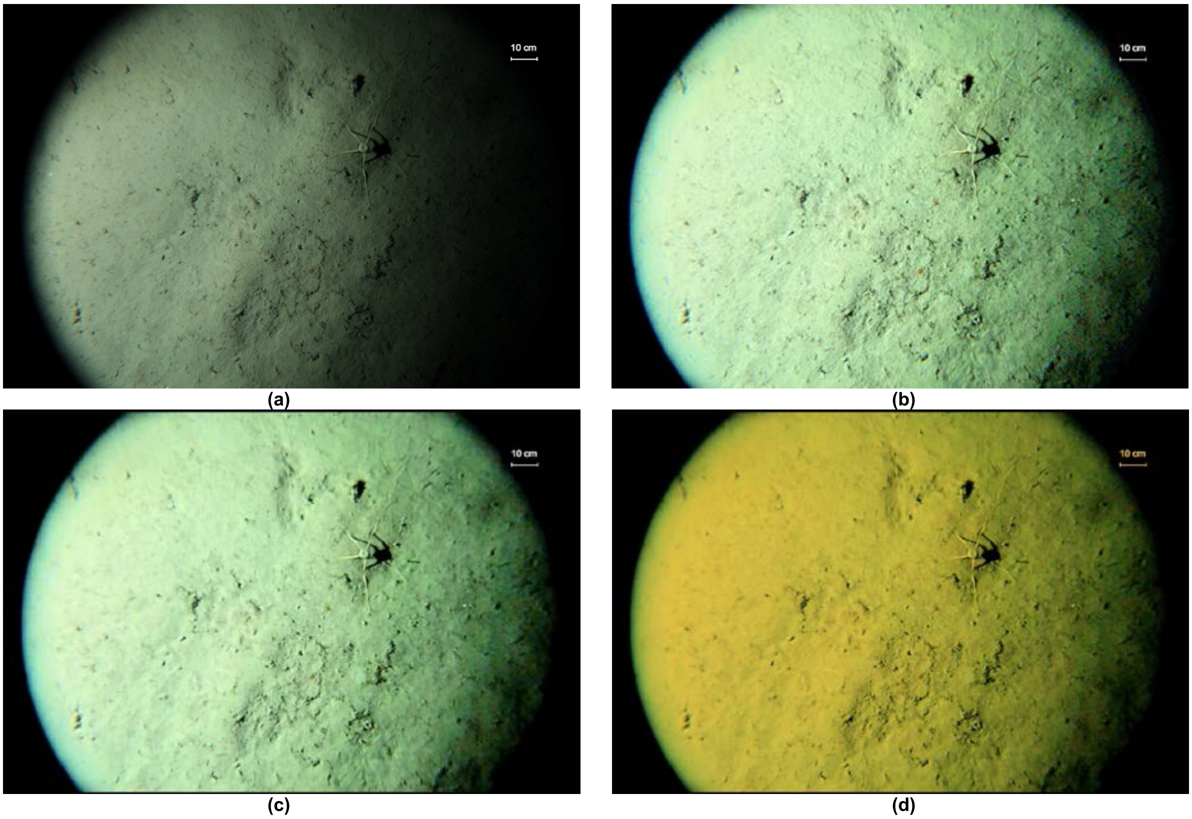


FIGURE 1. Deep-sea "Ophiuroidea." (a) Captured image. (b) Low-light enhanced image. (c) Denoised image. (d) Color corrected image.

$\iint F(x, y)dxdy = 1$; the smaller the scale σ is, the larger the dynamic range compression is, and the local details of the image are more obvious. The larger the scale σ, the better the overall effect of the image and the better the color recovery, but the details are easily lost.

It can be seen from Eq. (7) and (8) that the reflected light component of the image is expressed as:

$$R(x, y) = \log I(x, y) - \log [I(x, y) * F(x, y)] \tag{10}$$

At this time, $R(x, y)$ is a component of the logarithmic domain. The image we need is in the real number field, so we have to convert $R(x, y)$ as follows:

$$r(x, y) = exp(R(x, y)) \tag{11}$$

D. GAMMA CORRECTION

Gamma correction is also a widely used and cost-effective contrast enhancement method [13]. Its basic form can be formulated as:

$$\mathrm{T}(\ell) = \ell_{max}(\frac{l}{l_{max}})^{\gamma} \tag{12}$$

where ℓ_{max} is the maximum intensity of the input and the intensity ℓ of each pixel in the input image is transformed as $\mathrm{T}(\ell)$ after performing. As expected, the gamma curves illustrated with $\gamma > 1$ have exactly the opposite effect as those generated with $\gamma < 1$.

However, in the experiment, the authors did not use the underwater images or simulated underwater images. There are 3 disadvantages of this work:

1) The atmospheric imaging model is unsuitable for underwater imaging;

2) There were no underwater low-light images for experiments;

3) Color distortions and noise exist in the processed images.

III. PROPOSED METHOD

To improve upon the above-mentioned method, we propose a bright channel model, and a corresponding denoising algorithm and color correction method.

A. BRIGHT CHANNEL MODEL

In this paper, we define the inverted image of an underwater image as

$$R_c^{\lambda}(x) = 255 - I_c^{\lambda}(x) \tag{13}$$

where c is the color RGB channels. $I_c^{\lambda}(x)$ is the intensity of a color channel of pixel x of the low lighting image at wavelength λ. $R_c^{\lambda}(x)$ is the same intensity of the inverted image. The scattered image is modelled as

$$R^{\lambda}(x) = J^{\lambda}(x)\, t(x) + A^{\lambda}(1 - t(x)) \tag{14}$$

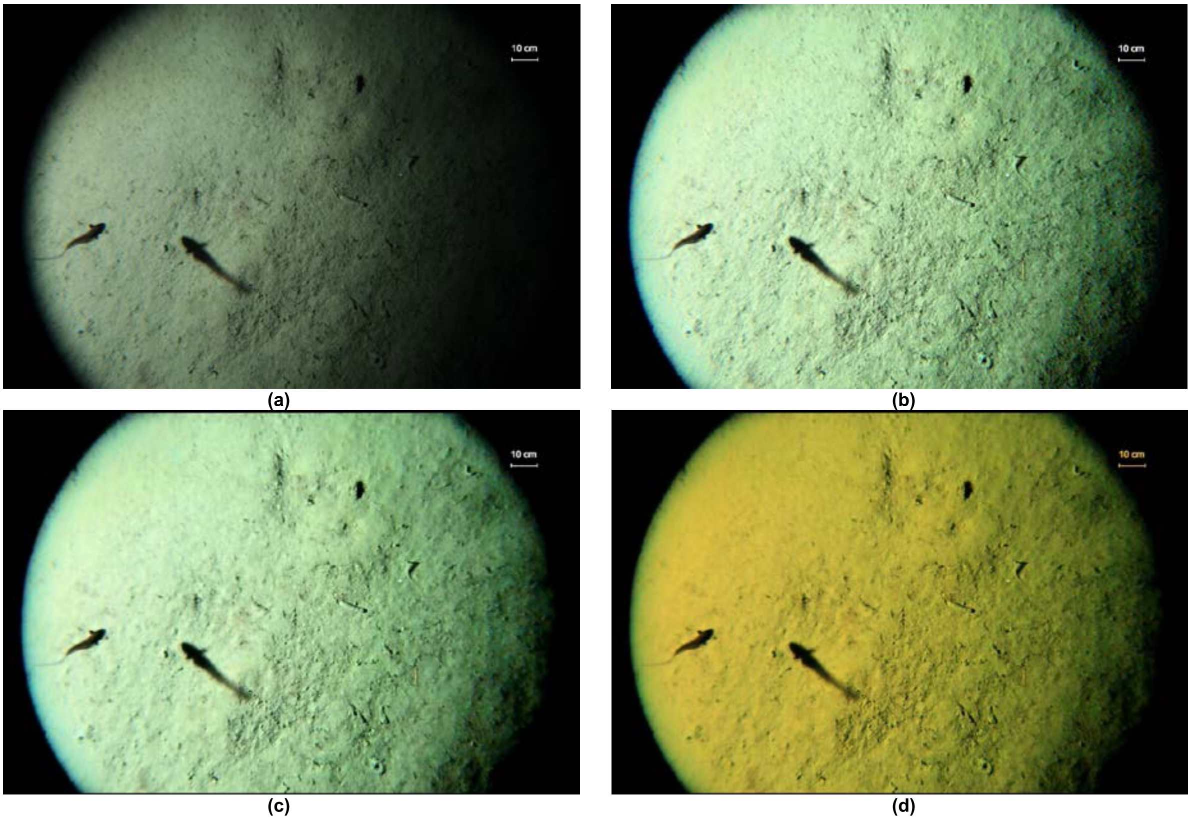


FIGURE 2. Deep-sea "fish." (a) Captured image. (b) Low-light enhanced image. (c) Denoised image. (d) Color corrected image.

where A^{λ} is the global veiling light. The transmission map $t(x)$ can be estimated by

$$t\left(x\right)=1-\omega\min_{c\in R,G,B}(min_{y\in\Omega(x)}(R_c^{\lambda}(y)/A^{\lambda})) \tag{15}$$

B. TRANSMISSION MAP REFINEMENT

In above, we propose the method for estimating the coarse transmission map. For remove the scatter, it is needed to refine the transmission map Therefore, we propose to develop a guided filter to reduce such mosaic effects. The normalized image is obtained as follows:

$$R_c^f\left(x\right)=\begin{cases}\dfrac{R^{\lambda}\left(x\right)-R_{min}^{\lambda}(x)}{R_{max}^{\lambda}\left(x\right)-R_{min}^{\lambda}(x)}, & 0<R^{\lambda}\left(x\right)<1\\ 0, & R^{\lambda}\left(x\right)<0\\ 1, & 1<R^{\lambda}\left(x\right)\end{cases} \tag{16}$$

The refinement of the filtered joint is first performed under the guidance image $R_c^f(x)$. Here, let $d_p(x)$, $d_q(x)$, $R_{c,p}^f(x)$ and $R_{c,q}^f\left(x\right)$ be the intensity value at the pixel p, q of the transmission map and the guidance image, respectively, while w_k is the kernel window centred at pixel k. The refined transmission map is then formulated as:

$$R\left(x\right)=\frac{1}{\sum_{q\in w_k}W_{pq}(R_c^f(x))}\sum\nolimits_{q\in w_k}W_{pq}(R_c^f(x)d_q(x)) \tag{17}$$

where the kernel weight function $W_{pq}(R_c^f(x))$ is expressed as:

$$W_{pq}\left(R_c^f\left(x\right)\right)=\frac{1}{|w|^2}\sum\nolimits_{k:(p,q)\in w_k}\times\left(1+\frac{(R_{c,p}^f\left(x\right)-\mu_k)(R_{c,q}^f\left(x\right)-\mu_k)}{\sigma_k^2+\varepsilon}\right) \tag{18}$$

where μ_k and σ_k^2 are the mean and variance of the guidance image in the local window w_k, respectively, and $|w|$ is the number of pixels in this window. After the refined depth map is obtained, we can recover the real scene using the underwater dark channel prior descattering model.

C. DENOISING

In this paper, we adapt vector deep convolutional neural networks for underwater denoising. In [14], the target image is divided into a batch of samples indexed by j and the minibatch training with a convolution layer is defined by

$$[f_i^{l+1}]_i=\sigma\left([\varphi_c(f_{,j}^l)]_j\left[w_i^l\right]_i+[b_i^l]_i\right) \tag{19}$$

where $[]_j$ is to assemble the matrix of different samples. This method can speed up the computing time.

D. COLOR CORRECTION

After denoising, the colors are seriously distorted. In order to recover the real color of underwater scene, we adapt the

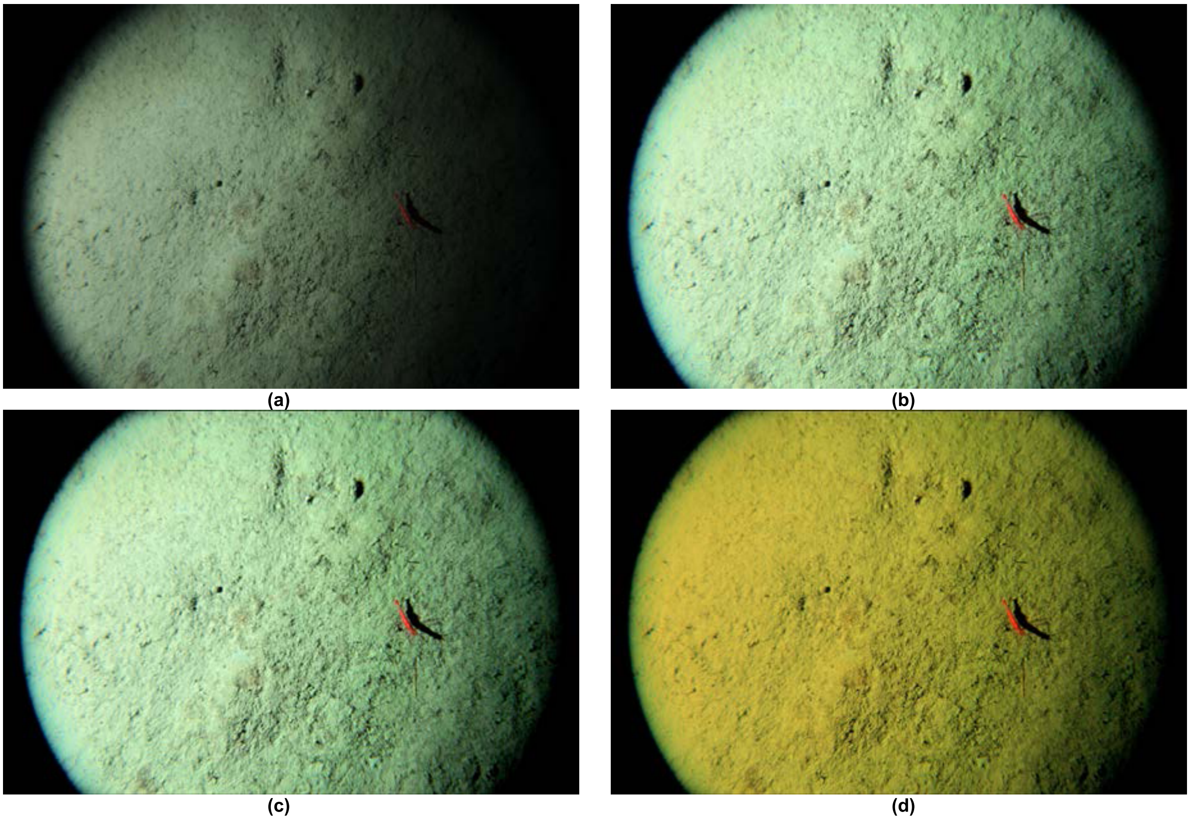


FIGURE 3. Deep-sea "Lobster." (a) Captured image. (b) Low-light enhanced image. (c) Denoised image. (d) Color corrected image.

spectral characteristics-based color correction method to address the color distortion issue [22]. We take the chromatic transfer function τ to weight the light from the surface to a given depth of objects as follows:

$$\tau_\lambda = \frac{E_\lambda^{surface}}{E_\lambda^{object}} \tag{20}$$

where the transfer function τ at wavelength λ is derived from the irradiance of the surface $E_\lambda^{surface}$ by the irradiance of the object E_λ^{object}. According to the spectral response of the RGB camera, we convert the transfer function to the RGB domain as follows:

$$\tau_{RGB} = \int_{400nm}^{725nm} \tau_\lambda \cdot C_c(\lambda) \tag{21}$$

where the weighted RGB transfer function is τ_{RGB}, and $C_c(\lambda)$ is the underwater spectral characteristic function of the color band c, $c \in \{r, g, b\}$. Finally, the corrected image is gathered from the weighted RGB transfer function as follows:

$$J_\lambda^c(x) = \nu_{RGB} \cdot \hat{J}_\lambda^c(x) \cdot \tau_{RGB} \tag{22}$$

where $J_\lambda^c(x)$ and $\hat{J}_\lambda^c(x)$ are the color-corrected and uncorrected images respectively. ν_{RGB} is the spectral power distribution transfer function.

TABLE 1. Quantitative analysis of the proposed method.

	Colourfulness	Sharpness
Image 1	1.6535	2.3580
	5.8051	3.5149
Image 2	1.6544	2.4178
	5.6862	3.4027
Image 3	1.8087	1.2574
	5.5745	1.6282
Image 4	1.7070	2.5190
	5.5699	3.6060
Image 5	1.9082	1.3933
	5.4784	1.8444

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

We tested the proposed method with images of real-world, deep-sea observation systems. The images used were captured by the free-ascending tripod (fat), which was built at tongji university in china and is used to monitor in situ sediment movement. Fat was recovered in late september 2014 after spending about six months collecting data on the floor of the northeastern south china sea (scs). The enhanced images are characterized by a reduced noise level with better exposure in dark regions and improved global contrast, by which the finest details and edges are significantly enhanced, demonstrating the effectiveness of the proposed method. Figure 1 to figure 3 show the recovered results of the images.

From the above experimental results, we find the proposed method removed the electrical noise and corrected the color distortions of the radiometric compensation in water. Except the visual measurement by human, we also compared the recovered image with the captured image by quantitative analysis [21]. Table 1 shows the good performance of the proposed method.

V. CONCLUSION

As described in this paper, we built a dedicated camera system and corresponding image processing technologies for in situ deep-sea observation in the South China Sea. The proposed method can improve the quality of deep-sea images. It can remove unwanted particles, correct non-uniform illumination, recover real-scene color, and provide super-resolving of the images. Real-world experiments demonstrated that the proposed system performs better than existing methods. It can be concluded that the proposed methods are suitable for ocean observation.

REFERENCES

[1] H. Lu, Y. Li, Y. Zhang, M. Chen, S. Serikawa, and H. Kim, "Underwater optical image processing: A comprehensive review," *Mobile Netw. Appl.*, vol. 22, no. 6, pp. 1204–1211, 2017.

[2] J. Y. Chiang and Y.-C. Chen, "Underwater image enhancement by wavelength compensation and dehazing," *IEEE Trans. Image Process.*, vol. 21, no. 4, pp. 1756–1769, Apr. 2012.

[3] R. Fattal, "Dehazing using color-lines," *ACM Trans. Graph.*, vol. 34, no. 1, pp. 1–10, 2014.

[4] H. Lu, Y. Li, L. Zhang, and S. Serikawa, "Contrast enhancement for images in turbid water," *J. Opt. Soc. Amer. A*, vol. 32, no. 5, pp. 886–893, 2015.

[5] J. Li, K. A. Skinner, R. M. Eustice, and M. Johnson-Roberson, "WaterGAN: Unsupervised generative network to enable real-time color correction of monocular underwater images," *IEEE Robot. Autom. Lett.*, vol. 3, no. 1, pp. 387–394, Jan. 2018.

[6] X. Yu, Y. Qu, and M. Hong, "Underwater-GAN: Underwater image restoration via conditional generative adversarial network," in *Proc. Int. Conf. Pattern Recognit.*, 2018, pp. 66–75.

[7] C. Fabbri, M. J. Islam, and J. Sattar, "Enhancing underwater imagery using generative adversarial networks," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2018, pp. 7159–7165.

[8] J. Lu, N. Li, S. Zhang, Z. Yu, H. Zheng, and B. Zheng, "Multi-scale adversarial network for underwater image restoration," *Opt. Laser Technol.*, vol. 110, no. 1, pp. 105–113, 2019.

[9] T. P. Marques, A. B. Albu, and M. Hoeberechts, "Enhancement of low-lighting underwater images using dark channel prior and fast guided filters," in *Proc. ICPR Workshops*, 2019, pp. 55–65.

[10] T. Fan, C. Li, X. Ma, Z. Chen, X. Zhang, and L. Chen, "An improved single image defogging method based on Retinex," in *Proc. 2nd Int. Conf. Image, Vis. Comput. (ICIVC)*, Chengdu, China, Jun. 2017, pp. 410–413.

[11] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 3rd ed. Publishing House of Electronics Industry, 2017, pp. 72–77.

[12] D. J. Jobson, Z. Rahman, and G. A. Woodell, "Properties and performance of a center/surround retinex," *IEEE Trans. Image Process.*, vol. 6, no. 3, pp. 451–462, Mar. 1997.

[13] G. Cao, Y. Zhao, R. Ni, and X. Li, "Contrast enhancement-based forensics in digital images," *IEEE Trans. Inf. Forensics Security*, vol. 9, no. 3, pp. 515–525, Mar. 2014.

[14] J. S. Ren and L. Xu, "On vectorization of deep convolutional neural networks for vision tasks," in *Proc. 29th AAAI Conf. Artif. Intell.*, 2015, pp. 1840–1846.

[15] H. Lu, Y. Li, T. Uemura, H. Kim, and S. Serikawa, "Low illumination underwater light field images reconstruction using deep convolutional neural networks," *Future Gener. Comput. Syst.*, vol. 82, pp. 142–148, May 2018.

[16] H. Lu *et al.*, "CONet: A cognitive ocean network," *IEEE Wireless Commun.*, to be published.

[17] Y. Li, H. Lu, K.-C. Li, H. Kim, and S. Serikawa, "Non-uniform de-scattering and de-blurring of underwater images," *Mobile Netw. Appl.*, vol. 23, pp. 352–362, Apr. 2018.

[18] Y. Li, H. Lu, J. Li, X. Li, Y. Li, and S. Serikawa, "Underwater image de-scattering and classification by deep neural network," *Comput. Elect. Eng.*, vol. 54, pp. 68–77, Aug. 2016.

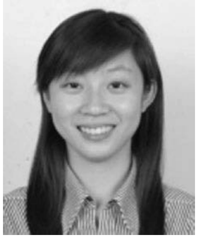
[19] H. Lu, Y. Li, S. Nakashima, and S. Serikawa, "Turbidity underwater image restoration using spectral properties and light compensation," *IEICE Trans. Inf. Syst.*, vol. E99.D, no. 1, pp. 219–227, 2016.

[20] S. Serikawa and H. Lu, "Underwater image dehazing using joint trilateral filter," *Comput. Elect. Eng.*, vol. 40, no. 1, pp. 41–50, 2014.

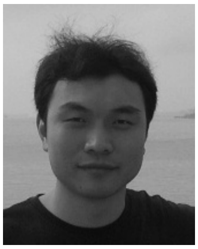
[21] K. Panetta, C. Gao, and S. Agaian, "Human-visual-system-inspired underwater image quality measures," *IEEE J. Ocean. Eng.*, vol. 41, no. 3, pp. 541–551, Jul. 2015.

[22] J. Li and Y. Li, "Underwater image restoration algorithm for free-ascending deep-sea tripods," *Opt. Laser Technol.*, vol. 110, pp. 129–134, Feb. 2019.

[23] J. Li and Y. Li, "Guided local laplacian filter-based image enhancement for deep-sea sensor networks," *Multimedia Tools Appl.*, vol. 77, no. 9, pp. 10823–10834, 2018.



YUJIE LI received the B.S. degree in computer science and technology from Yangzhou University, in 2009, the M.S. degree in electrical engineering from the Kyushu Institute of Technology and Yangzhou University, in 2012, and the Ph.D. degree from the Kyushu Institute of Technology, in 2015. She is currently a Lecturer with Yangzhou University. Her research interests include computer vision, sensors, and image segmentation.



JIANRU LI is currently an Assistant Professor with the State Key Laboratory of Marine Geology, Tongji University, China. He is also a Marine Geologist by training. His M.S. and Ph.D. theses addressed the effect of variations in the Earth's orbit (or orbital forcing) on the ocean carbon cycle.

YUN LI received the M.Eng. degree in computer science and technology from the Hefei University of Technology, in 1991, and the Ph.D. degree in control theory and control engineering from Shanghai University, in 2005. He is currently a Professor with the School of Information Engineering, Yangzhou University, China, where he is also a Vice Dean of the School of Information Engineering. His research interests include pattern recognition, information fusion, data mining, and cloud computing.

HYOUNGSEOP KIM received the B.A. degree in electrical engineering and the master's and Ph.D. degrees from Kyushu Institute of Technology, in 1994, 1996, and 2001, respectively, where he is currently a Professor with the Department of Control Engineering. His research interest includes the medical application of image analysis.

SEIICHI SERIKAWA received the B.S. and M.S. degrees from Kumamoto University, in 1984 and 1986, respectively, and the Ph.D. degree from the Kyushu Institute of Technology, in 1994, all in electronic engineering. He is currently a Vice President of the Kyushu Institute of Technology and also serves as a Professor with the Center for Socio-Robotic Synthesis and the Department of Electrical and Electronic Engineering. His current research interests include computer vision, sensors, and robotics.