# A Fast and Efficient Atmospheric Light Estimator for Underwater Image Dehazing

I-Chang Huang, Shiann-Rong Kuang, Ying-Jhou Syu, and Hsiang-An Hsieh
Department of Computer Science and Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan
Email: d122543064@gmail.com, srkuang@cse.nsysu.edu.tw

***Abstract*—Atmospheric light and transmission estimations are the most important steps in underwater image dehazing based on dark channel prior. In this paper, we develop a fast and efficient method to estimate the atmospheric light according to the red channel prior for underwater image dehazing. The subsampling technique is first applied to reduce the computational complexity of atmospheric light estimation with almost no visual quality degradation. Accordingly, a low-cost VLSI architecture with heavy resource sharing for the atmospheric light estimation is proposed to meet the requirement of real-time underwater image dehazing. Compared to previous design, the proposed atmospheric light estimator requires much less hardware cost and can achieve 2.3 times speedup while maintaining good visual quality.**

***Index Terms*—underwater image dehazing, dark channel prior, atmospheric light estimation, VLSI architecture**

## I. Introduction

Recently, people have paid more and more attention to the study of undersea due to the growing shortage of natural resources on land. When exploring the underwater environment, video or images are usually utilized to obtain the valuable information. Unfortunately, underwater images usually suffer from poor visibility and low contrast because of the phenomena of optical scattering and absorption in water. Furthermore, underwater images also have the problem of color distortion because the light attenuation is associated with the wavelength of spectrum. In general, the shorter wavelengths (green and blue colors) can reach greater depths under the water than the longer wavelengths (red color), leading to the underwater images with a typical bluish or greenish tone as shown in Fig. 1. For practical applications, poor visibility and color distortion will seriously affect the exploration of underwater environment.

To overcome this problem, the restoration of hazy images with image processing techniques has been researched in various ways. For example, Schechner *et al.* [1] analyzed the physical effects of visibility degradation and proposed an algorithm based on a couple of images obtained through a polarizer that is rotated to work at different orientations. As a result, extra information about the scene that facilitates the inversion of the image formation process can be acquired. Moreover, Torres-Mendez *et al.* [2] presented a supervised algorithm, where parameters of color correction are learnt over training data. However, the above-mentioned methods require extra information and do not work on a single image. To avoid the problem of multiple images, several single-image methods have been developed to remove haze for single image. Fattal [3] presented a method for estimating the optical transmission in foggy scenes based on minimal input to increase scene visibility and recover haze-free scene contrasts. He *et al.* [4] introduced an effective method named the dark channel prior to remove haze from a single image. In [4], the concept of dark channel was first applied to estimate the atmospheric light and the transmission from the input hazy image. Afterward, the soft matting method was used in [4] to optimize the transmission to avoid the halo artifact generated in the recovered scene. Finally, the scene without haze can be recovered from the atmospheric light and optimized transmission. However, soft matting has very high computational complexity and requires heavy computing resource. Therefore, He *et al.* [5] proposed the guided filter instead of the soft matting to refine the estimated transmission effectively. The guided filter has a nice property of edge-preserving smoothing and lower computational complexity.

Figure 1. Typical underwater image.

Since the situation of degraded underwater images is similar to the effect of hazy weather on outdoor vision, several recent researches (e.g., [6]-[12]) have extended and improved the dark channel prior method to restore the visual quality of underwater images while considering the nature of the degradation induced by a marine environment. For instance, Chiang *et al.* [7] enhanced the

Manuscript received December 28, 2018; revised February 25, 2019.

underwater images by joining a dehazing method with wavelength compensation. According to the estimation of wavelength attenuation, a reverse compensation was conducted to restore the color distortion. Galdran *et al.* [10] considered the absorption effect in the red channel and proposed a red channel prior method. This method is simple and robust, and can restore the red color with short wavelengths, leading to a contrast improvement.


Figure 2. General flowchart of underwater image dehazing.

However, most of the above-mentioned underwater image dehazing methods require high computing resource and long execution time when they are implemented in software. Consequently, these methods are probably unsuitable for real-time applications and integrated systems. To meet the real-time requirements, Shiau *et al.* [13] proposed a fast method and the corresponding pipelined hardware architecture for haze removal based on the concept of a dark channel. The proposed architecture in [13] can perform atmospheric light estimation, transmission estimation, and scene recovery. In addition, Huang *et al.* [14] presented a low-complexity guided filter and its low-cost hardware implementation to refine the estimated transmission of underwater images. This simplified guided filter can support Full-HD underwater image dehazing at a throughput of 30 frame/s.

In addition to transmission estimation, atmospheric light estimation is also an important step in underwater image dehazing based on dark channel prior. Although the achievable throughput is very high, the hardware architecture of the atmospheric light estimator proposed in [13] is expensive. Therefore, this paper proposes a fast and efficient method and its low-cost VLSI architecture to estimate the atmospheric light based on the red channel prior [10] for underwater image dehazing. We first apply the subsampling technique with a subsampling ratio of $s$ to significantly reduce the computational complexity of atmospheric light estimation to $1/s^2$ without obvious visual quality degradation. As a result, the corresponding hardware architecture can heavy share the computation resources while keeping a very high performance to decrease the hardware cost significantly. Compared to the atmospheric light estimator in [13], the proposed architecture consumes much less hardware cost and can achieve 2.3 times speedup and the comparable visual quality.

The remainder of this paper is organized as follows. In Section II, the background information and related methods for underwater image dehazing are introduced briefly. Then, the proposed atmospheric light estimation method and hardware architecture are presented in Section III. The experimental results and comparisons are described in Section IV. Finally, the conclusion is provided in Section V.

## II. BACKGROUND

Clear and brilliant underwater image is essential to many applications such as ocean engineering, ocean science, and ocean biology etc. As mentioned previously, many image dehazing systems have been proposed to improve the visual quality of underwater images based on the concept of dark channel prior method. Fig. 2 illustrates a general flowchart of underwater image dehazing, which is based on the common and popular optical model shown in (1). In this model, the input hazy image $I$ is modeled as two components: the direct transmission of light from the object and the transmission due to turbid water medium and floating particles, as follows.

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

where $I$ is the observed (hazy) image on the three RGB color channels, $J$ is the scene radiance, $t$ is the transmission along the ray, and $A$ is the global atmospheric (background) light. The first term $J(x)t(x)$ is treated as direct attenuation and the second term $A(1 - t(x))$ denotes airlight.

Using this optical model to recover the scene $J$, the main challenge is to estimate the atmospheric light $A$ and the transmission $t$ from the hazy image $I$ properly. The transmission can be expressed as $t(x) = e^{-\beta d(x)}$, where $\beta$ is the scattering coefficient of the atmosphere and $d$ is the scene depth at $x$. Unfortunately, it is difficult to compute $t(x)$ from $e^{-\beta d(x)}$ directly. Instead, the dark channel prior method proposed in [4] can be used to estimate atmospheric light and the transmission. The dark channel of image $I$ can be obtained by

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

where $I^c$ is a color channel of image $I$ and $\Omega(x)$ is a local patch centered at $x$. Afterward, the atmospheric light can be estimated from the top 0.1% brightest pixels in the dark channel $I^{dark}$. Moreover, according to dark channel prior method, the intensity value of $J^{dark}$ is low and tends to be zero if the scene $J$ is a haze-free image. In addition, the transmission in a local patch $\Omega(x)$ is supposed to be a constant. After rewriting (1) and applying (2) to (1), the transmission can be estimated as

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

where $\omega$ is a constant parameter and is used to keep a small amount haze.

However, this estimated transmission $\tilde{t}(x)$ in (3) is coarser and requires a smoothing operator to preserve its edges. The guided filter [5], which is an edge-preserving image filter and can effectively avoid gradient reversal artifacts with lower computational complexity, can be adopted to refine $\tilde{t}(x)$ into $t(x)$. After $A$ and $t$ have been obtained, the desired scene radiance $J$ can be recovered as

$$J(x) = \frac{I(x)-A}{\max(t(x), t_0)} + A \quad (4)$$

where $t_0$ is a lower bound used to restrict $t(x)$ to avoid the noise generated in the recovered scene.

In fact, the red color component usually undergoes maximum attenuation in an underwater environment. Therefore, several recent works (e.g., [10]) for underwater image dehazing modified the dark channel prior according to the absorption effect in the red channel to enhance the restoration performance. Galdran *et al.* [10] proposed a red channel method and modified the red channel of optical model in (1) into

$$1 - I^r(x) = \big(1 - J^r(x)\big)t(x) + (1 - A^r)\big(1 - t(x)\big) \quad (5)$$

Based on the same idea, the red channel of original image $I$, denoted by $I^{red}(x)$, is computed as

$$I^{red}(x) = \min\big(\min_{y\in\Omega(x)}(1 - I^r(y)), \min_{y\in\Omega(x)} I^g(y), \min_{y\in\Omega(x)} I^b(y)\big) \quad (6)$$

Afterward, the atmospheric light can be obtained from $I^{red}(x)$, and the transmission can be estimated as

$$\tilde{t}(x) = 1 - \min\left(\min_{y\in\Omega(x)} \frac{1-I^r(y)}{1-A^r}, \min_{y\in\Omega(x)} \frac{I^g(y)}{A^g}, \min_{y\in\Omega(x)} \frac{I^b(y)}{A^b}\right) \quad (7)$$

Finally, the scene radiance $J$ is recovered as

$$J(x) = \frac{I(x)-A}{\max(t(x), t_0)} + (1 - A)A \quad (8)$$

For more details about red channel prior, please refer to [10]. Nevertheless, the recovered underwater images usually has color distortion after dehazing due to the discrepancy absorption of different lights. To obtain better recovery images, the color correction methods (e.g., [15]) can be applied after scene radiance recovery to achieve the balanced color values of the RGB components.

## III. Proposed Atmospheric Light Estimator

As can be seen in (3), (4) and Fig. 2, the atmospheric light $A$ must first be obtained from the input image $I$ for estimating the transmission and recovering the scene $J$. He *et al.* [4] picked the top 0.1% brightest pixels from the dark channel $I^{dark}$, and selected a suitable value from these brightest pixels as the atmospheric light. However, the sorting process to find the atmospheric light is time-consuming and the sorting time will depend on the size of an input image. To meet the requirement for real-time applications, Shiau *et al.* [13] proposed an approximate method and the corresponding hardware architecture to find the atmospheric light quickly. After $I^{dark}$ has been obtained, a maximum value $A^{dark}$ is determined as

$$A^{dark} = \max_{(i,j)\in I}\{I^{dark}(i,j)\} \quad (9)$$

where max is the maximum operation to find the maximum value of $I^{dark}$ at $(i,j)$ coordinate. If the pixel $A^{dark}$ is located at $(s,t)$ coordinate, the corresponding pixel value of $I$ at $(s,t)$ coordinate is found as the candidate of atmospheric light. Subsequently, an adjustment parameter $\theta$ is applied to refine the atmospheric light as follows.

$$A^c = \theta \cdot I^c(s,t), \ \forall c \in (r,g,b) \quad (10)$$

The parameter $\theta$ can be regarded as an intensity correction for the recovered scene adjustment. In [13], $\theta$ is set to 0.875 so that it can be implemented by using shift operation.

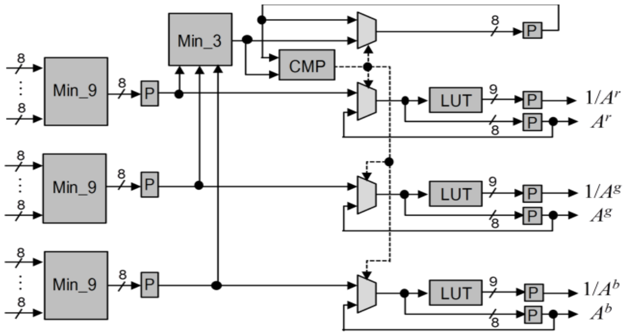



Figure 3. Architecture of atmospheric light estimator in [13].

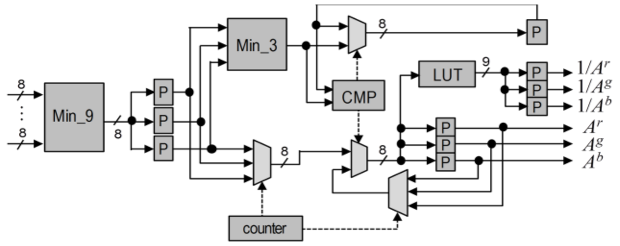



Figure 4. Architecture of the proposed atmospheric light estimator.

Fig. 3 illustrates the hardware architecture of atmospheric light estimator proposed in [13]. In Fig. 3, the Min_9 unit determines a minimum value from nine pixel values of a 3×3 window and the Min_3 unit determines a minimum value among three color channels. The CMP unit finds a maximum value as the atmospheric light. The value of $1/A^c$ is calculated by a look-up table (LUT) unit. The architecture in Fig. 3 is a two-stage pipelined architecture and can process one pixel each clock cycle to estimate the atmospheric light. That is, it would take about 2,073,600 clock cycles and 20.7 ms to process a Full-HD image with 1920×1080 pixels if the architecture can operate at 100MHz.

Although the achievable performance is quite high, the hardware architecture of the atmospheric light estimator proposed in [13] is expensive. In this paper, we apply the subsampling technique with a subsampling ratio of $s$ to reduce the computational complexity of atmospheric light estimation to $1/s^2$, so that its hardware architecture can be further simplified. To achieve the goal, the input image $I$ is first subsampled into $I'$. In order to avoid complicating the subsampling process, we directly pick the pixel in the top left corner of an $s$×$s$ window of input image $I$ as the subsampled pixel. Then, $I'^{dark}$ and $A'^{dark}$ of the subsampled image $I'$ can be obtained as

$$A'^{dark} = \max_{(i,j)\in I'}\{I'^{dark}(i,j)\} \quad (11)$$

Assume that $s$ = 4, the computational complexity of atmospheric light estimation can be reduced to 1/16. Accordingly, a low-cost hardware architecture as shown in Fig. 4 is proposed to estimate the atmospheric light. In the proposed architecture, only one Min_9 unit and one LUT unit are required and its critical path delay is the same with that of the architecture in Fig. 3. Moreover, it takes seven clock cycles to deal with one pixel, and would take about 907,200 clock cycles and 9.1 ms to process a Full-HD image with 1920×1080 pixels if the architecture can operate at 100MHz. The comparisons between the architectures in Fig. 3 and Fig. 4 for processing a Full-HD image are summarized in Table I. The results show that the proposed architecture consumes less hardware cost and is 2.3 times faster than the architecture in Fig. 3.

TABLE I. COMPARISON BETWEEN DIFFERENT ATMOSPHERIC LIGHT ESTIMATOR FOR PROCESSING A FULL-HD IMAGE

| ALT Design | Shiau [13] | Proposed |
|---|---|---|
| # of Min_9 | 3 | 1 |
| # of LUT | 3 | 1 |
| # of Min_3 | 1 | 1 |
| # of CMP | 1 | 1 |
| latency | 2 | 7 |
| # of clock cycles | 2,073,600 | 907,200 |

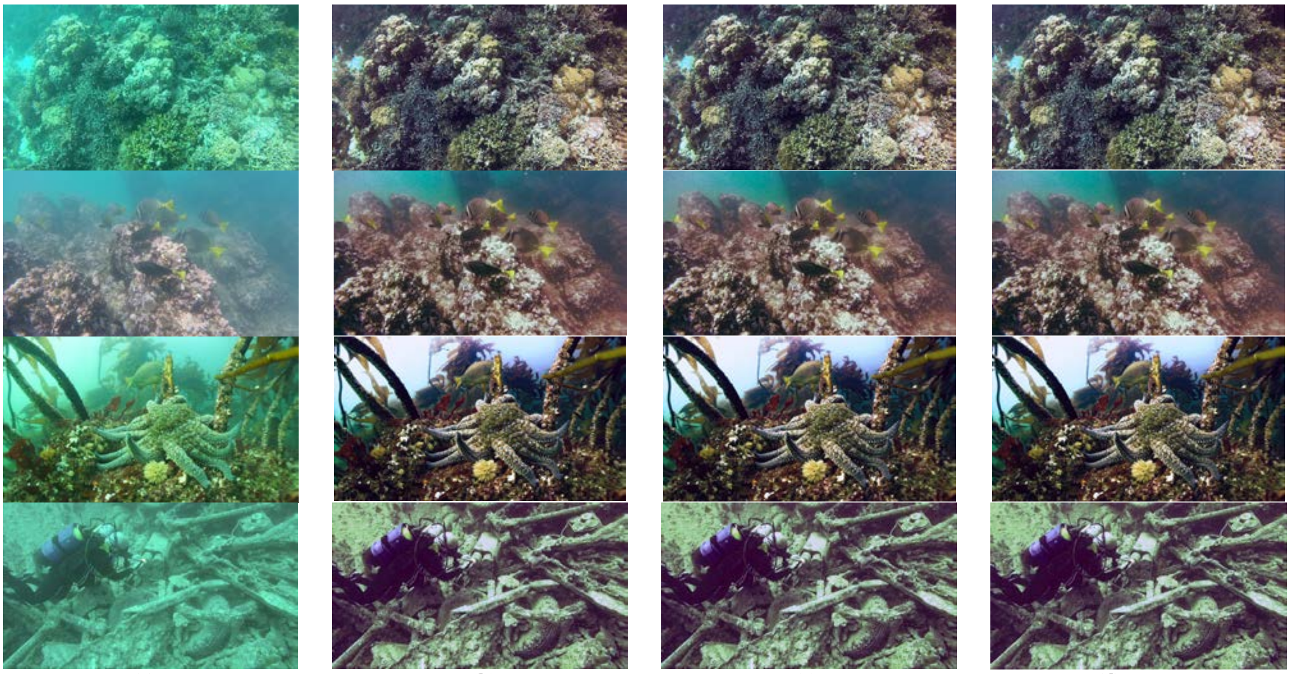
## IV. EXPERIMENTAL RESULTS

To evaluate the visual quality of the proposed atmospheric light estimator (ALE), an underwater image dehazing system similar to Fig. 1 was implemented in C++ language with single-precision floating-point (FP) format. In this experiment, three versions of dehazing system were developed for comparison. The first version (Dehazing_SW) adopted the red channel prior in [10], atmospheric light estimation in [13], guided filter in [5], and was implemented in software with FP format. In the second version (ALE_HW), the atmospheric light estimation in the first version was replaced by the proposed atmospheric light estimator implemented in SystemC with the fixed-point format and $s$ = 4. In the third version (ALE_GF_HW), the guided filter (GF) in the second version was replaced by the simplified GF proposed in [14] implemented in SystemC with the fixed-point format. Several Full-HD underwater images (Image 01 to Image 12) in different water conditions and different scene configurations were used for the experiments. The output results of Image 01 to Image 04 shown in Fig. 5 demonstrate that ALE_HW and ALE_GF_HW can obtain the comparable results to Dehazing_SW.

In addition to the aforementioned qualitative comparison, the quantitative evaluation was carried out to further evaluate the visual quality of proposed ALE. Table II shows the entropy comparisons among different versions. The value of entropy represents the valuable information contained in the recovered images. In addition, the peak-signal-to-noise (PSNR) value and the structural similarity (SSIM) index [16] among the underwater images produced by Dehazing_SW and other versions are also calculated and listed in Table II. As can be seen in Table II, the average entropy of different version is almost the same, and all PSNR values are higher than 60 dB. Moreover, all SSIM indices are larger than 0.97. The results in Table II exhibit that the visual quality produced by ALE_HW and ALE_GF_HW is very close to that of Dehazing_SW.

TABLE II. QUANTITATIVE COMPARISON OF DIFFERENT DEHAZING SYSTEMS IN TERMS OF ENTROPY, PSNR AND SSIM

| Images | Dehazing_SW | ALE_HW | | | ALE_GF_HW | | |
|---|---|---|---|---|---|---|---|
| | Entropy | Entropy | PSNR | SSIM | Entropy | PSNR | SSIM |
| Image 01 | 5.251 | 5.242 | 92.52 | 0.9978 | 5.241 | 91.50 | 0.9971 |
| Image 02 | 6.366 | 6.392 | 88.71 | 0.9982 | 6.393 | 87.85 | 0.9974 |
| Image 03 | 6.408 | 6.405 | 115.37 | 0.9994 | 6.404 | 103.19 | 0.9973 |
| Image 04 | 6.135 | 6.146 | 106.85 | 0.9992 | 6.141 | 105.31 | 0.9978 |
| Image 05 | 5.837 | 5.809 | 66.12 | 0.9749 | 5.812 | 65.93 | 0.9731 |
| Image 06 | 6.39 | 6.422 | 101.64 | 0.9932 | 6.421 | 97.71 | 0.9923 |
| Image 07 | 5.642 | 5.644 | 87.55 | 0.9986 | 5.646 | 86.59 | 0.9973 |
| Image 08 | 6.493 | 6.475 | 85.57 | 0.9765 | 6.475 | 85.29 | 0.9769 |
| Image 09 | 5.689 | 5.700 | 113.51 | 0.9982 | 5.703 | 107.72 | 0.9970 |
| Image 10 | 6.539 | 6.539 | 129.66 | 0.9994 | 6.547 | 108.45 | 0.9936 |
| Image 11 | 6.462 | 6.454 | 112.36 | 0.9980 | 6.464 | 100.58 | 0.9959 |
| Image 12 | 6.519 | 6.552 | 81.94 | 0.9845 | 6.554 | 81.17 | 0.9846 |
| Average | 6.144 | 6.148 | 98.48 | 0.9932 | 6.150 | 93.44 | 0.9917 |



(a) (b) (c) (d)

Figure 5. Qualitative Comparison of different designs (a) Original underwater images with a size 1920×1080, from top to bottom: Image 01, Image 02, Image 03, and Image 04, (b) Dehazing results by Dehazing_SW, (c) Dehazing results by ALE_HW, and (d) Dehazing results by ALE_GF_HW.

## V. Conclusion

This paper has proposed a fast and efficient atmospheric light estimator and its low-cost hardware architecture to achieve the real-time Full-HD underwater image dehazing while maintaining good visual quality. The subsampling technique was employed to reduce the computational complexity of atmospheric light estimation. As a result, the hardware resources can be heavy shared, leading to significant reduction in the hardware cost. Compared to previous design, the proposed architecture consumes less hardware cost and achieves higher performance without visual quality degradation.

## Acknowledgment

This work was supported in part by the Ministry of Science and Technology and the MOST AI Biomedical Research Center, Taiwan, under Grant MOST 107-2634-F-110-001 and MOST 107-2321-B-110-001.

## References

[1] Y. Schechner and N. Karpel, "Recovery of underwater visibility and structure by polarization analysis," *IEEE Journal of Oceanic Engineering*, vol. 30, no. 3, pp. 570-587, 2005.

[2] L. A. Torres-Mendez and G. Dudek, "Color correction of underwater images for aquatic robot inspection," in *Proc. 5th international conference on Energy Minimization Methods in Computer Vision and Pattern Recognition*, 2005, pp. 60-73.

[3] R. Fattal, "Single image dehazing," *ACM Transactions on Graphics*, vol. 27, no. 3, pp. 1-9, 2008.

[4] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 33, no. 12, pp. 2341-2353, 2011.

[5] K. He, J. Sun, and X. Tang "Guided image filtering," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 35, no. 6, pp. 1397-1409, 2013.

[6] H. Y. Yang, P. Y. Chen, C. C. Huang, Y. Z. Zhuang, and Y. H. Shiau, "Low complexity underwater image enhancement based on dark channel prior," in *Proc. Second International Conference on Innovations in Bio-inspired Computing and Applications*, 2011, pp. 17-20.

[7] J.-Y. Chiang and Y.-C. Chen, "Underwater image enhancement by wavelength compensation and dehazing," *IEEE Transactions on Image Processing*, vol.21, no.4, pp.1756-1769, 2012.

[8] R. Sathya, M. Bharathi, and G. Dhivyasri, "Underwater image enhancement by dark channel prior," in *Proc. 2nd International Conference on Electronics and Communication Systems (ICECS)*, 2015, pp. 1119-1123.

[9] H. Zheng, X. Sun, B. Zheng, R. Nian, and Y. Wang, "Underwater image segmentation via dark channel prior and multiscale hierarchical decomposition," in *Proc. OCEANS 2015 – Genova*, 2015, pp. 1-4.

[10] A. Galdran, D. Pardo, A. Picon, and A. Alvarez-Gila, "Automatic red-channel underwater image restoration," *Journal of Visual Communication and Image Representation*, vol. 26, pp. 132-145, Jan. 2015.

[11] C. Y. Cheng, C. C. Sung, and H. H. Chang, "Underwater image restoration by red-dark channel prior and point spread function deconvolution," in *Proc. IEEE International Conference on Signal and Image Processing Applications* (*ICSIPA*), 2015, pp. 110-115.

[12] S. J. Horng, P. J. Liu, and J. Sh. Lin, "Improving the contrast enhancement of oceanic images using modified dark channel prior," in *Proc. International Symposium on Computer, Consumer and Control*, 2016, pp. 801-804.

[13] Y. H. Shiau, H. Y. Yang, P. Y. Chen, and Y. Z. Chuang, "Hardware implementation of a fast and efficient haze removal method," *IEEE Transactions on* Circuits and Systems for Video Technology, vol. 23, no. 8, pp. 1369-1374, 2013.

[14] I. C. Huang, C. H. Chang, M. F. Lin, H. H. Chen, and S. R. Kuang, "Hardware implementation of an efficient guided image filter for underwater image restoration," *International Journal of Signal Processing Systems*, vol. 5, no. 3, pp. 94-99, 2017.

[15] M. Wu, K. Luo, J. Dang, and D. Li, "Underwater image restoration using color correction and non-local prior," in *Proc. OCEANS 2017 – Aberdeen*, 2017, pp. 1-5.

[16] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Trans. on Image Processing*, vol. 13, no. 4, pp. 600-612, 2004.

**I-Chang Huang** received the B.S. degree and M.S. degree in computer science and engineering from National Sun Yat-sen University, Kaohsiung, Taiwan, in 2016 and 2018, respectively. He is currently a full-time research assistant with the Department of Computer Science and Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan. His research interests include VLSI architecture design of image processing and digital signal processing.

**Shiann-Rong Kuang** received the B.S. degree from National Central University, Jhongli, Taiwan, in 1990, and the M.S. and Ph.D. degrees from National Cheng Kung University, Tainan, Taiwan, in 1992 and 1998, respectively, all in electrical engineering. He is currently a Professor with the Department of Computer Science and Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan. His current research interests include low-power/high-performance VLSI architectures for public-key cryptosystems and digital signal processing systems.

**Ying-Jhou Syu** received the B.S. degree in information engineering and computer science from Feng Chia University, Taichung, Taiwan, in 2017. He is currently working toward the M.S. degree at the Department of Computer Science and Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan. His research interests include VLSI architecture design of image processing and deep learning accelerator.

**Hsiang-An Hsieh** received the B.S. degree in computer science and engineering from National Sun Yat-sen University, Kaohsiung, Taiwan, in 2017. He is currently working toward the M.S. degree at the Department of Computer Science and Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan. His research interests include VLSI architecture design of image processing and deep learning accelerator.