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A NOVEL APPROACH FOR UNDERWATER IMAGE ENHANCEMENT BASED ON IMPROVED DARK CHANNEL PRIOR WITH COLOUR CORRECTION

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Abstract

The quality of underwater images is affected by characteristics of the underwater environment, such as varying light intensity levels and varied wavelengths. Low quality of underwater images is one of the major problems in identification of fish species during monitoring of underwater ecosystem. Improving the quality of underwater images is important for accurate fish identification. Some researchers introduce various methods that address colour-correction problem for underwater images. However, previous researches do not consider the noises produced during the implementation of the image processing techniques. To deal with this problem, we propose a novel method called novel contrast-adaptive colour-correction (NCACC) to enhance the quality of underwater images that are susceptible to bright colour distortion and various noises. The NCACC method is a combination of an automatic level correction and a limited contrast mode of adaptive histogram equalization method to be applied to the dark channel prior method. As a result, we are able to improve the contrast of the images without generating many noises. The experimental results show that the NCACC method significantly improves the quality of the underwater images. The improvement was assessed using the peak signal-to-noise ratio that yielded the value of 22.076 dB, which was 4.4% higher than the highest value obtained by the state-of-the-art method. We demonstrate that enhancement of underwater images is essential to reveal the detail of underwater objects.

Keywords: Auto-level colour-correction, Contrast limited adaptive histogram equalization, Dark channel prior, Underwater image processing.

1. Introduction

Indonesia is a maritime country with the largest sea area in the world. The sea area includes 17,504 islands, 95,181 km of coastlines, and 6.49 million square km sea area [1]. The sea area gives a beautiful, unique, and diverse underwater life in Indonesia, as well as providing various economic and ecological potentials. According to The World Bank [2] and Lembaga Ilmu Pengetahuan Indonesia (LIPI) [3], Indonesia faces a large threat to its underwater life due to its large sea area. Among all threatened marine ecosystem, fish is the most endangered marine ecosystem [4], with 158 fish species are endangered in Indonesia and more than 8,124 fish species are endangered in the world.

Many efforts have been made to reduce the impact of species extinction in the marine ecosystem, including the use of computer vision for marine ecosystem monitoring and underwater objects classification [5]. The technology automatically analyses and identifies underwater objects captured by a particular sensor, such as an RGB or a near-infrared sensor. However, because the process of object identification is solely based on underwater images, this technology highly depends on the observed underwater condition [6].

Clear images with minimum noises are required for accurate observation of underwater ecosystem. Nevertheless, as there is no light in the underwater environment, additional illumination from the camera's light is necessary during image acquisition. The underwater absorption of the light causes a decreased amount of light energy, while the scattering of the light in the water changes the direction of the incoming light. The absorption of the light is yielded by the partial polarization that occurs horizontally. On the other hand, the other part of the reflected light enters the water vertically, increasing the radiance. Hence, capturing a colour in a certain water depth level is more feasible while doing the same process in different depth level is challenging [7].

The density of the water is another problem for developing underwater image processing techniques. The density of the water is 800 times greater than the density of the air. The water molecules absorb a certain amount of light. Therefore, when the light travels through the air to the water, the surface of the water reflects some of the light and passes the rest [8]. As explained by Pujiono et al. [7], the density of the water causes the amount of light entering the water decreases gradually. Hence, the underwater images are getting darker as the deepness increases. Figure 1 displays variation of light reflection in the surface.

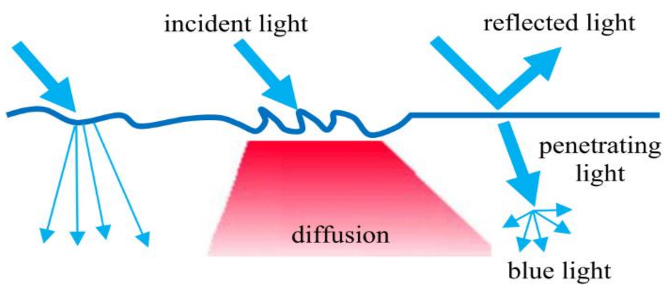

Fig. 1. Variation of light reflection in underwater environment.

Moreover, the colour of underwater objects changes with the increment of the depth level. Figure 2 shows colour degradation with regards to the depth of water. The long-wavelength colours disappear as the depth increases. Thus, only the short-length dark colours appear in the deep water [5]. Blue is the colour with the shortest wavelength, and the blue colour is abundant in the deep water. Therefore, images captured in the deep water are blurry with low brightness and contrast. The red colour disappears at the 3 m depth, followed by orange at the 5 m depth. The yellow colour vanishes at the 10 m depth. The green and purple colours fade as the depth increases [8].

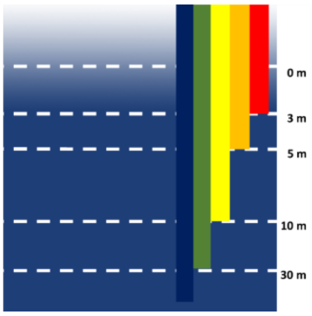

Fig. 2. Colour appearance in the underwater environment.

The disappearance of various colours causes underwater images to be lower in quality, brightness, contrast, and visibility. Furthermore, underwater images seem foggy [9]. As introduced by Yang et al. [10], these problems are solved by the dark channel prior (DCP) method. However, this method does not deal with removing blur at parts of an object that are exposed to a bright light. This weakness has been addressed by other researchers. For instance, Kaur and Mahajan [11] develop a colour correction method to deal with the trade-off of DCP method. To the best knowledge of the authors, the proposed method also generates many noises. To fill these research gaps, we propose a novel contrast-adaptive colour-correction (NCACC) method to improve the quality of underwater images without increasing the noise or causing over-enhancement. NCACC method is able to make the edges of the object in the image disappears; the texture of the image will change and form a rough detail in the image. NCACC method has several advantages, such as improving the quality of underwater images without degrading the image quality nor improving it excessively. Additionally, the proposed method is able to repair the quality of underwater images with low visibility, low brightness, and low contrast.

2. Previous Work

Many image-processing methods have been developed to improve the image quality. Chambah et al. [12] proposed an approach to improve image quality using automatic colour equalization method, which implements all image information with colour equalization. Meanwhile, Iqbal et al. use an integrated colour-model based on the contrast value [8] and an unsupervised colour-correction method with colour balancing and contrast correction [13]. Both studies of Iqbal et al. aim to find an efficient method to eliminate low-illumination and to show the real colour of underwater images. In another study, Pujiono et al. [7] proposed a model using the contrast limited adaptive histogram equalization (CLAHE) method to improve the quality of underwater images. The CLAHE can improve the visual quality of the image based on the improvement of MSE value. The CLAHE does not only repair the contrast but also equalizes the image histogram efficiently. Hence, the method improves the visibility of underwater images [14].

On the other hand, Yussof et al. [15] stated that the results generated from the CLAHE method have many noises. The CLAHE method is further developed by incorporating a colour combination model to partially reduce the noise and to repair the contrast, which improves the images quality. Pramunendar et al. [6] proposed an auto level method to solve the problem in case an image needs more contrast, while it has several shades of colour, therefore, the noise does not appear in all images. Meanwhile, Ancuti et al. [16] presented a combination of gamma correction and direct sharpening techniques of a real image after the image undergoes a white-balancing technique to restore faded features and edges. The sharpening method improves the contrast, but the method generates many noises if the sharpening method is done improperly [17]. Many studies have developed colour-correction methods for underwater images, but these methods merely depend on the image formation, which means the methods only modify the image pixel value without having additional information of the image scene depth [18].

Various studies have used the image depth to repair the foggy effect, such as the fog in underwater images that occurs due to light dispersion in the water. Carlevaris-Bianco et al. [19] proposed a model using DCP method to improve the quality of foggy underwater images, where the depth coefficient in this method is determined by the image attenuation coefficient. Meanwhile, Yang et al. [10] applied the combination of the DCP method to estimate the surrounding light, the median filter to obtain the depth of the image, and the contrast colour-correction to improve the quality of underwater images. Wen et al. [20] used green and blue layers-without the red layer-to define a dark channel for complementing underwater images.

Different from Wen et al. [20], Galdran et al. [21] proposed a method to restore faded colour in underwater images using the red layer. Kaur and Mahajan [11] suggested a combination of the DCP method and the CLAHE method to improve the distorted image contrast. Meanwhile, Li and Gou [22] used a combination of the dark channel prior method and histogram equalization to improve the image quality. Previous methods based on the dark channel prior can be applied in the underwater images. Although the problems of the dark channel prior methods can be solved with our proposed method, we also have to deal with noise suppression. Therefore, an improvement to reduce the generated noises from the previous methods is an essential scientific contribution for research of underwater object recognition.

3. NCACC Approach

An underwater image generally has low visibility, low brightness, and low contrast while also seems foggy. To solve these problems, we propose a simple and effective approach to improve the quality of underwater images. The flowchart of the NCACC method is displayed in Fig 3. In this research, we also aim to improve the results of previous studies [9, 11]. The NCACC approach consists of several steps. First, we apply an approach based on the lowest intensity of the foggy effect in the underwater image using one of the RGB colour layers. The intensity of the pixel is used to estimate the transmission map of the foggy effect. Then, the foggy effect in the underwater image is removed using the model generated from the transmission map and the interpolation method. Next, the auto level colour-correction method and the CLAHE method are implemented simultaneously. The novelty of our NCACC method is a technique to adaptively improve the contrast without generating excessive noises on underwater images. Therefore, processed the images will produce informative features that are useful in underwater object recognition.

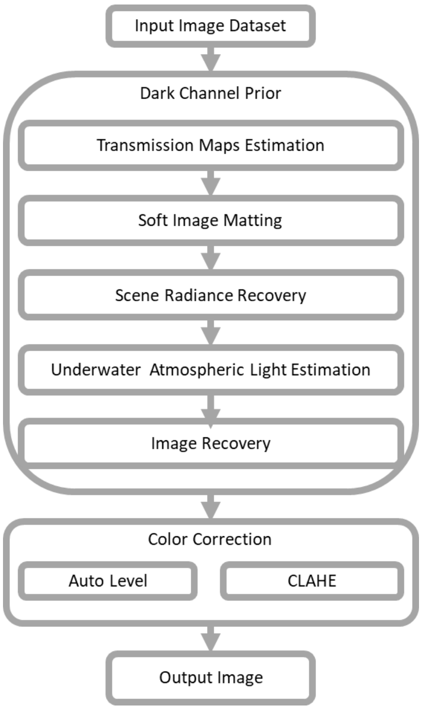

Fig. 3. The NCACC method.

3.1. Image dataset

In this study, we assume that the underwater condition in Indonesia is similar to other locations in the world. Hence, the underwater images used in this study were obtained from LifeCLEF 2014 (LCF-14), known as Fish4Knowlege dataset. The dataset Fish4knowledge was downloaded from http://groups.inf.ed.ac.uk/f4k/. We used the dataset because it provides suitable problems that can be solved using the NCACC method. The dataset comprises of 27,370 images of various fishes' images with foggy background caused by underwater colour domination. The images have varied size with an average size of 100 × 100 pixels.

3.2. Dark channel prior

In underwater images, the fog thickness determines the water depth. The dark channel prior (DCP) method has been used to eliminate the foggy effect in the underwater images [9]. The DCP method is an outdoor fog-free image statistic that contains pixels with very low intensity in one colour layer. The method estimates the fog thickness to calculate the distance between an object and the camera by which, the surrounding light intensity is approximated.

If $J(im)$ is a foggy image and $t(im)$ is a transmission medium, the blur level of an image can be formulated using Eq. (1).

$$I(im) = J(im)t(im) \tag{1}$$

As the aim of the dark channel prior image is restoring *J* from *I*, when symbol *A* and *t* are approximated from *I, J* can be calculated using Eq. (2).

$$J(im) = \frac{I(im)-A}{t(im)} + \tag{2}$$

In the outdoor fog-free image characteristic, there are dark pixels with the intensity close to zero [23]. Therefore, the dark channel is defined using Eq. (3).

$$J^d(im) = \min_{y\epsilon\Omega(im)} \left(\min_{c\epsilon\{r,g,b\}} J^c(imy) \right) \tag{3}$$

With J^c is the colour intensity on the layer of an RGB image, while $\Omega(im)$ is the center of the local patch on pixel im. The minimum values of three colour layers in all pixels in $\Omega(im)$ are selected as the dark channel $J^d(im)$. The low intensity of the dark channel is caused by the image shadow, saturated-colour objects, and dark objects in the image.

3.2.1. Transmission maps estimation through dark channel prior

This approach by He et al. [18] is based on the study that uses one of the R, G, and B layers on the local area in fog-free images with low intensity and light intensity ranging in small numbers. The foggy area reduces the quality of the object in the image. Assuming that there are the atmospheric light A and a constant local transmission patch $\Omega(im)$, the initial transmission can be expressed by Eq. (4).

$$\tilde{t}(im) = 1 - \min_{c} \left(\min_{y\epsilon\Omega(im)} \frac{I^c(imy)}{A^c} \right) \tag{4}$$

As explained by He et al. [18], dark channel prior is not optimal to be used in the sky area because it has the same colour with atmospheric light *A* in the fog image. Thus, this condition has a zero transmission value. In this study, the concept in Eq. (4) is used to determine the atmospheric light *A* in the underwater image data. Meanwhile, Lee et al. [23] stated that the generated image may seem unnatural if all fogs are removed. Therefore, a small value of constant parameter ω $(0 < \omega \leq 1)$ is added to Eq. (5) to mark the residual fog image. In this study, all inputs are analysed to determine the best ω value to obtain the optimum image quality.

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

3.2.2. Soft image matting

Filtering methods such as Gaussian and bilateral filters are effective to remove fake colour textures in the transmission map. However, results of the depth map must have a high sharpness to be used in perfecting the transmission map. Based on the study conducted by He et al. [18], we also implement soft image matting to repair the transmission map and to fix the white-balancing problem, which estimates values of the unknown area. Using Eq. (6), we repair the transmission map $t(im)$ with L is the length of matting matrix, and λ value is used to control data.

$$E(t) = t^T L t + \lambda(t - \tilde{t})^T (t - \tilde{t}) \quad (6)$$

Using a linear system based on U or identity matrix in the same size as L, the optimum value of t is obtained using Eq. (7). The size of U in this study uses the smallest value (10^{-4}) to get the optimum value of t.

$$\lambda\tilde{t} = (L + \lambda U)t \quad (7)$$

3.2.3. Scene radiance recovery

In the generated transmission map, scene radiance is formulated in Eq. (1). He et al. [18] explained that the data $J(im)$ is susceptible to noise. Therefore, the data should have a transmission limit $t(im)$ to the lower limit $t(0)$. The updated scene radiance value $J(im)$ after recovery process is obtained using Eq. (8).

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

3.2.4. Atmospheric light estimation

Estimation of air-light in A as the atmospheric light value is assumed to have a certain number. Thus, using an estimation of transmission $\tilde{t}$, the air light value is determined. Carlevaris-Bianco et al. [19] state that the pixel's minimum transmission estimation represents the furthest image from the camera. Then the intensity of the real image location is used to estimate the air light. The pixel with the highest intensity in the image is selected as air light.

3.3. Auto level colour correction

Auto level colour-correction is the process to stretch histogram [24], which is a simple way to improve the quality of the image [6]. The process is done by determining the minimum (im_{min}) and the maximum (im_{max}) values for all pixels using Eq. (9).

$$\partial = c(im_{max} - im_{min})$$
$$w_{max} = I(im)_{max} + \partial$$
$$w_{min} = I(im)_{min} + \partial$$
$$I(im)' = \frac{255}{w_{max} - w_{min}}(im - w_{min}) \quad (9)$$

$I(im)$ is the input image, c is the coefficient in percent, ∂ is the generated colour coefficient, and $I(im)'$ is the resulting image. The auto level colour-correction process in a colour image is done separately for each colour layer.

3.4. Contract limited adaptive histogram equalization (CLAHE)

The contrast limited adaptive histogram equalization (CLAHE) has been proven to be able to intensify low-contrast images [25]. CLAHE classifies images based on contextual fields and implements histogram equalization for each field. At the beginning of the CLAHE method, the image is divided into some regions with the equal size. Next, CLAHE calculates the histogram for every region. A clip limit for clipping histograms is obtained using Eq. (10). Thereafter, every histogram is redistributed using a distribution function if it does not go through the clip limit. At last, cumulative distribution functions of the resultant CLAHE are determined for grayscale mapping.

$$\beta = \frac{MN}{L}\left(1 + \left(\frac{\alpha}{100}(S_{max} - 1)\right)\right) \tag{10}$$

In Eq. (10), α is the clip limit factor, while M and N are the region size and grayscale value. Moreover, S_{max} is a maximum allowable slope, respectively. The distribution function of pixel histogram in CLAHE can be classified to the uniform distribution, exponential distribution, and Rayleigh distribution. The resulting histogram of the uniform distribution has a flat histogram as shown in Eq. (11). Meanwhile, the exponential distribution is spread on the higher frequency that produces a curved histogram as formulated in Eq. (12), while the Rayleigh distribution has the distribution in the middle level of grayscale that produces a bell-shaped histogram as shown in Eq. (13).

$$g = [g_{max} - g_{min}] * P(f) + g_{min} \tag{11}$$

$$g = g_{min} - \left(\frac{1}{\alpha}\right) * ln[1 - P(f)] \tag{12}$$

$$g = g_{min} + \left[2\alpha^2\, ln\left(\frac{1}{1-P(f)}\right)\right]^{\frac{1}{2}} \tag{13}$$

Furthermore, g_{max} is the maximum pixel value and g_{min} is the minimum pixel value, whereas g and $P(f)$ are the calculated pixel value and the cumulative probability distribution, respectively.

3.5. Image quality assessment

Image quality assessment is conducted using two methods consisting of peak signal to noise ratio (PSNR) and patch-based contrast quality index (PCQI).

3.5.1. Peak signal to noise ratio

Peak Signal to Noise Ratio (PSNR) [26] is a quality measurement that is calculated based on two pieces of the comparable image to observe the level of mismatch between the images. PSNR value is obtained using Eq. (14), with the $I(im)$ is an original image and $J(im)$ is an enhanced image.

$$PSNR = 10\, log_{10}\left(\frac{MAX^2}{\frac{1}{num\ of\ pixel}\sum\sum\left(I(im) - J(im)\right)^2}\right) \tag{14}$$

3.5.2. Patch-based contrast quality index

Patch-based Contrast Quality Index (PCQI) [27] is used to calculate the structural similarity index between two pieces of an image object based on luminance, contrast and data structure. PCQI value is obtained using Eq. (15). Image assessment using PCQI is similar to structural similarity index (SSIM), but the value can be larger than one when the signal strength is enhanced. The quality of the image is degraded even the value of PCQI smaller than one.

$$PCQI(x, y) = \frac{1}{M}\sum_{j=1}^{M} PCQI(x_j, y_j)$$

$$PCQI(x, y) = q_i(x, y) * q_c(x, y) * q_s(x, y)$$

$$q_i(x,y) = e^{-\frac{c_1^x - c_1^y}{\sqrt{N}L}}$$
$$q_s(x,y) = (c_2^y + r^T v_2)$$
$$q_c(x,y) = \frac{4}{\pi} * arctan\left|\frac{c_2^y}{c_2^x}\right| \quad (15)$$

q_i describes the comparison of mean intensities, q_s describes the ratio of the average structure and q_c is a comparison of the average quality of the contrast value. The c_1^x, c_2^x, v_1 and v_2 describe the average intensity, signal strength, and signal structure, respectively. c_1^x and c_2^x are equal to c_1^y and c_2^y, while r is a vector residue that is 0.

4. Design of Experiment

Prior state-of-the-art methods were applied to image samples from the fish4knowledge dataset. The state-of-the-art methods were dark channel prior (DCP), auto level colour-correction (ALCC), contrast limited adaptive histogram equalization (CLAHE), auto white balance (AWB), and the combination of some of those methods as suggested in [11]. The combination consists of DCP method and ALCC method (DCPALCC), DCP method and CLAHE method (DCPCLAHE), and DCP method and AWB method (DCPAWB). The performance of the prior methods was compared with our proposed method (NCACC). Sample data were taken randomly from the dataset. Then, the performance of each state-of-the-art method on recovering images was compared with the NCACC method using two evaluation matrices: peak signal-to-noise ratio (PSNR) and patch-based contrast quality index (PCQI) [27].

5. Results and Discussion

5.1. Visual evaluation

Table 1 shows the visual comparison of underwater images using various image enhancement methods. The results show that the DCP method could enhance the image quality, but not all pixels were improved. Meanwhile, the CLAHE method enhanced the objects' edge to give the feature of the image, but this method generated excessive noise. The noise generated by the CLAHE method depended on the neighbourhood of the pixel and the set clipping parameter values. This happened because CLAHE took action in blocks that might be overlapping on the implementation and neighbourhood of a pixel-pixel histogram in the image that ordered how the pixel value was mapped to a new value for that image. Noise could have more contrast on a sharper image on the sharp edges. The AWB method improved the images' colour by reducing several other colours, but blur images appeared after the colour lose. Lastly, the ALCC method enhanced the contrast in each colour layer. The NCACC method was able to improve the image quality without generating many noises.

Table 2 shows the v4isual comparison of the combination of the previous methods and the NCACC method that generated the feature of each colour layer. The results show that the combination of DCP and the other methods could enhance the image, but the NCACC method was able to enhance the image without significant changes compared with the original image.

Table 1. Visual comparison of several image enhancement methods.

Image enhancement methods	Image No. 1	Image No. 2	Image No. 3
Original			
ALCC			
CLAHE			
AWB			
DCP			
NCACC			

Table 2. Visual comparison of several combined image enhancement methods.

Image enhancement methods	Image No. 1	Image No. 2	Image No. 3
DCP-ALCC			
DCP-CLAHE			
DCP-AWB			
NCACC			

5.2. Performance evaluation

The evaluation metrics were used to analyse the effectiveness of the proposed method (NCACC) compared with prior state-of-the-art methods. The experimental results show that the NCACC method yielded good performance in improving the quality of underwater images. The NCACC method was able to reveal the features of the underwater objects. Table 3 shows the comparative analysis of PSNR from several image enhancement methods on 100 out of 230 underwater images. This data was taken randomly from the dataset. The results on Table 3 show that images that were enhanced using DCP method often had better quality than images that were enhanced with the other methods. However, experimental results show that some DCP images tend to become blurred images when they were exposed to bright light. Therefore, not all images processed by the DCP method were transformed to images with better quality. Hence, the average value of PSNR of DCP method was lower than the average value of the NCACC method.

On the other hand, the result of the comparison of PSNR from several combined methods in Table 4 shows that the NCACC method yielded the highest PSNR value. Moreover, the NCACC method produced the highest average PSNR compared with the other methods (as shown in Fig. 4). The results of each method (as shown in Table 3) such as ALCC, CLAHE, AWB and DCP produce PSNR of 19.6831dB, 17,8336dB, 16,9755dB and 21,0952dB, respectively. The combination of DCP-ALCC, DCP-CLAHE and DCP-AWB (as shown in Table 4) produce PSNR of 17.2793dB, 15.6352dB, and 14.3087dB, respectively. The average PSNR of all sample images by the NCACC method was 4.4% (22.076 dB) higher than the highest PSNR value of previous methods (DCP method). That is the NCACC method provides the best results of image quality than the other methods.

Evaluation using PCQI metric provides information on variation of image quality. PCQI result lower than 1 means that the image was degraded, as shown in Table 5. In contrast, the improvement of image quality was marked by PCQI higher than 1 [27]. We assumed that the value of 1 indicated a quality image. As can be seen in Fig. 5, the original DCP method yielded the smallest PCQI average of 1.0335. By calculating the difference from the centre value of one, the DCP had the smallest difference of 0.0335. However, the general observation of DCP method shows that its results sometimes had a decreased quality.

On the other hand, the NCACC method had an average PCQI of 1.051, which means that the PCQI result had a difference in the amount of 0.051 from the best value. This is because the assessment results provided by PCQI value is 1, if the original image is similar to the resulting image. PCQI is able to produce a value more than 1, if the image has an over enhancement. On the other side, it will be less than 1, if the image quality is degraded. Compared with CLAHE and DCP-CLAHE combination, the NCACC method was able to improve the quality of the images without causing over-enhancement. The PCQI values of the ALCC, AWB, DCP-ALCC, and DCP-AWB methods were lower than one, which means that these methods generated images with the degraded quality compared to the original images. As shown in Tables 5 and 6 also Fig. 5, we can conclude that CLAHE, DCP, DCP-CLAHE combination and the NCACC method were able to improve the image quality. Meanwhile, the ALCC, AWB, DCP-ALCC combination, and DCP-AWB combination methods changed the image quality by decreasing the quality of the original image.

Table 3. Comparison of PSNR of several image enhancement methods.

DATA	ALCC	CLAHE	AWB	DCP	NCACC
1	15.0127	25.2517	1.4899	22.0169	24.7717
2	20.7340	19.0243	0.8197	16.9467	21.2849
3	19.8129	17.2887	9.5972	30.4518	23.1409
4	18.3750	15.7008	11.3718	22.7232	21.4439
5	18.3790	18.2511	11.9136	20.9537	23.6551
6	17.8805	21.8401	21.5565	26.9307	25.8055
7	22.9009	17.6186	24.1299	20.3458	23.4589
8	18.1662	18.2697	12.9619	18.4557	20.6319
9	20.3245	17.4811	23.6642	18.2099	20.6845
10	17.0406	18.1509	10.5179	21.2853	22.4024
230	17.4124	16.5531	14.3588	17.7331	21.3142
Average	19.6831	17.8336	16.9755	21.0952	22.0761

Table 4. Comparison of PSNR of several combined image enhancement methods.

DATA	DCP-ALCC	DCP-CLAHE	DCP-AWB	NCACC
1	15.3220	17.8988	1.4899	24.7717
2	16.4883	13.3524	0.8197	21.2849
3	20.4630	17.2760	9.5814	23.1409
4	16.8366	14.6706	12.1647	21.4439
5	13.6574	15.4286	13.4138	23.6551
6	17.9965	19.4354	23.6824	25.8055
7	18.5564	15.4914	18.7932	23.4589
8	14.6642	14.4315	13.7933	20.6319
9	16.9614	12.3994	19.3593	20.6845
10	15.7414	14.3604	11.0620	22.4024
230	15.8661	12.7156	16.4503	21.3142
Average	17.2793	15.6352	14.3087	22.0761

Table 5. Comparison of PCQI of several image enhancement methods.

DATA	ALCC	CLAHE	AWB	DCP	NCACC
r	0.8715	1.1173	0.1998	1.0462	1.0764
2	0.9593	1.1074	0.1954	1.0425	1.0933
3	0.8878	1.0317	0.5618	0.9979	1.0137
4	0.9010	1.0578	0.8561	0.9707	1.0727
5	0.8587	1.1366	0.9128	1.0216	1.1072
6	0.9208	1.0042	0.9483	1.0175	1.0242
7	0.9308	1.0422	0.9155	1.0173	1.0655
8	0.9208	1.1412	0.9000	1.0130	1.1174
9	0.9766	1.0099	0.9109	1.0566	1.0723
10	0.8715	1.1173	0.1998	1.0462	1.0764
230	0.9042	1.1305	0.7767	0.9418	1.0990
Average	0.8825	1.1063	0.8253	1.0335	1.0509

Table 6. Comparison of PCQI of several combined image enhancement methods.

DATA	DCP-ALCC	DCP-CLAHE	DCP-AWB	NCACC
1	0.9646	1.0921	0.1998	1.0764
2	0.9987	1.0428	0.1954	1.0933
3	0.9239	1.0692	0.5403	1.0137
4	0.9280	1.1380	0.9167	1.0727
5	0.8857	1.1752	0.9708	1.1072
6	0.9603	1.0498	1.0064	1.0242
7	0.9803	1.0618	0.9289	1.0655
8	0.9731	1.0951	1.0319	1.1174
9	0.9974	0.9524	1.0312	1.0723
10	0.9646	1.0921	0.1998	1.0764
230	0.8953	1.0850	0.8508	1.0990
Average	0.9594	1.1312	0.8787	1.0509

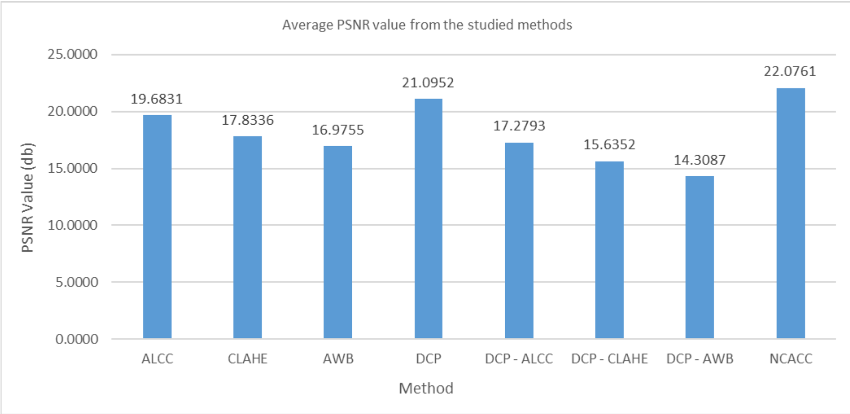

Fig. 4. Average PSNR values from the studied methods.

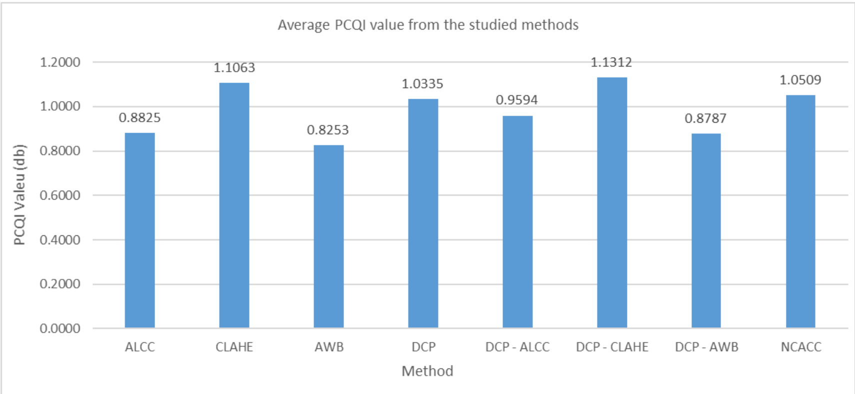

Fig. 5. Average PCQI values from the studied methods.

5.2. Discussion

Based on the results of visual comparison and analysis of evaluation metrics, we can conclude that the NCACC method was able to repair and to improve the quality of underwater images better than previous state-of-the-art methods. The enhanced images were sharp without generating many noises. Compared with the original DCP method, the NCACC method improves the sharpness of the image by reducing several bright colours. In the previous study [11], the quality of images produced by the DCP method is improved. The DCP method is used to remove fog in the images and to show the objects covered by the fog. However, the DCP method is susceptible to bright colours that generated a blurry image in a part with bright colours.

Additionally, previous work implements the DCP - CLAHE combination. This method can improve the quality of some parts in the images with bright colours. However, the combined method generates many noises. Therefore, our study uses a filtering method to reduce the number of noises (Table 2). The results show that the DCP - ALCC combination and DCP - AWB combination were able to repair the images, but these methods could not enhance the images. Meanwhile, the proposed method was able to improve the sharpness of some parts in the images with bright colours without generating many noises.

In addition to visual evaluation, the use of evaluation metrics shows that the NCACC method produced the highest PSNR value followed by the DCP method. This result demonstrates that the NCACC method was able to repair and to improve the quality of the images compared with the DCP method. In some images of the dataset, the DCP method produced better results than the NCACC method. In this case, there was no part with a bright colour that was caused by the fog. Therefore, the number of noises was different. The average PCQI value also shows that the NCACC method did not improve the quality of the images excessively. The NCACC method was able to repair the quality of underwater images with low visibility, low brightness, and low contrast. The NCACC method also improved the quality of foggy images. The limitation and disadvantage of our methods are only sharpened properties in the image front, which produces unbalance in the sharpened image. Thus, our future works will focus on finding a new method to sharpen the overall foggy images in underwater images. Nevertheless, the other researcher can use the NCACC method for improving the quality of the image before obtaining informative features, particularly in identifying underwater creatures.

6. Conclusions

Enhancement of underwater images is an important research topic for accurate fish identification using computer vision. Previous state-of-the-art methods have addressed the colour-correction problem for underwater images. However, previous research does not consider the noises produced during the implementation of the image processing techniques. To fill this research gap, we propose a novel approach to improve the quality of the underwater images. The proposed NCACC method is able to enhance the quality of underwater images. Experimental results show that the NCACC method neither degraded the image quality nor improved excessively. Our experiment result is similar to the statement from Kaur and Mahajan [11], that DCP method provides noise when the images are visually observed. Filtering method and CLAHE were used to reduce the noise produced by DCP and to restore the image without any blurring, the combination of DCP-CLAHE without applied filtering method even gave a lot of noise, and therefore, the research is dependent on the filtering method. While on NCACC, the auto level method is able to solve the problem of contrast adaptively without giving much noise to the image. The PSNR value of the NCACC method is 4.4% higher than the highest value obtained by the previous methods. Additionally, the NCACC method yielded PCQI value of 1.051 - with a difference of 0.051 to the value of one. Hence, the NCACC method produces an appropriate improvement while enhances features of the images better than the other state-of-the-art methods [9, 11]. In future, we aim to evaluate the effect of image improvement on the identification of underwater creatures.

Nomenclatures

A	Atmospheric light
A^c	Colour intensity on atmospheric light
c	coefficient in percent
$E(t)$	The transmission map
I^c	Colour intensity on $c\epsilon\{r, g, b\}$ image, uint8

I(im)	Image
J^c	Colour intensity on $c\epsilon\{r, g, b\}$ foggy image, uint8
J(im)	Foggy image or new image, uint8
L	Length of matting matrix
M	The region size
N	Grayscale value, uint8
t(im)	Transmission medium
$\tilde{t}(x)$	Initial transmission
∂	Generated colour coefficient -

Greek Symbols

α	Clip limit factor
λ	Value is used to control data
Ω	Constant local transmission patch
ω	Constant unnatural parameter

Abbreviations

ALCC	Auto Level Colour-Correction
AWB	Auto White Balance
CLAHE	Contrast Limited Adaptive Histogram Equalization
DCP	Dark Channel Prior
MSE	Mean Square Error, dB
PCQI	Patch-Based Contrast Quality Index, dB
PSNR	Peak Signal-To-Noise Ratio, dB
RGB	Red Green Blue

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