Coordinated underwater dark channel prior for artifact removal of challenging image enhancement*

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When dehazing underwater images, the patch-by-patch dark channel prior (DCP) method is frequently used. After the DCP-based processing, there are still some drawbacks, such as patch artifacts, and these artifacts will seriously affect the subjective quality of some challenging images. To remove the patch artifacts from the DCP-guided enhancement mechanism, this paper proposes a coordinated underwater dark channel prior (CUDCP) method. The proposed method considers the characteristics of the red-green-blue channels with different attenuation situations, and thus the attenuation ratios of the red-green-blue channels are adaptively coordinated in diverse images. The requirement for color restoration is then assessed by an evaluation criterion, and the color restoration is carried out by using the compensated gray world (CGW) theory, which further coordinates the intensity of various red-green-blue channels. Our method next applies a patch-division average filter in accordance with the sub-patch classification. On the typical dataset, the enhanced images of our CUDCP method have higher average underwater image quality measure (UIQM) scores (about 2.274 8) when compared with the original images and those of some state-of-the-art enhancement methods, while the computational cost of CUDCP (about 88.618 8 s) is slightly higher than that of the original DCP (about 87.493 8 s). The experimental results demonstrate that in comparison to state-of-the-art enhancement methods, the proposed method can significantly reduce patch artifacts in challenging image enhancement, while maintaining the objective quality of such underwater images, and also enhancing their subjective quality at a reasonable computational cost.

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Underwater imagery is becoming increasingly important with the increasing demand in the fields of fisheries, nuclear power plant underwater monitoring, land engineering in the sea, and diving. But there are far more factors affecting light propagation underwater than on land. As the underwater is full of humus, organic matter, and plankton, they will inevitably affect the propagation of light. For original underwater images, there are often defects such as blur, severe noise, low contrast, and color cast due to the shooting environment, especially for challenging underwater scenes[1]. Therefore, it has become a priority for researchers to make underwater images more realistic and clearer. Ref.[2] has some current reviews on underwater image enhancement. During underwater image enhancement, some areas will be oversaturated for those low-contrast images[3]. In addition, the dark channel prior (DCP) based methods always perform the enhancement patch-by-patch. If the correlation between patches is ignored, artifacts will appear on the edges of these patches[4].

To obtain better image results, HE et al[5] firstly established a DCP which may be used in various image restoration tasks. Since then, the DCP-based methods are successively proposed. Due to the similarity between underwater images and foggy images, it is feasible for the DCP method to process underwater images, but there are a number of important aspects to take into consideration. Because the underwater shooting environment is different from the land shooting environment, it is unreasonable to directly use DCP. A DCP-based variation that successfully incorporates the fast attenuation of red light in waterbody has been well-extended for underwater image enhancement[6]. When red light decays rapidly, the transmission map estimated by DCP will become the value of the red channel, which is not what the prior expects. Further, AKKAYNAK et al[7] created a Sea-thru method that estimates the backscattered light and optimizes the image imaging model in the DCP method to make the processed underwater image look like it is acquired on land.

In nearshore or open sea, and deep sea or shallow sea, different situations need be carefully distinguished.

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Therefore, the backscattered light is estimated by using the quartile strategy up until the target areas are chosen[8]. LIANG et al[9] provided a generalization of underwater dark channel prior (GUDCP) for underwater image enhancement. More importantly, the image processing with the GUDCP method has a different estimation of backscattered light than on land, as well as a different estimation of the transmission map. In addition, HOU et al[10] proposed a variational dark channel prior (VDCP) for underwater image enhancement. Although VDCP is based on the original DCP method, it uses a fast algorithm that makes the processing time even shorter than the original DCP method. However, the above DCP-guided enhancement will lead to patch artifacts that affect the subjective quality of enhanced images.

Enlightened by the GUDCP method, this paper firstly utilizes the intensity of the red-green-blue (RGB) channels to determine the attenuation ratio of the relevant channel, and thus obtains a severely attenuated channel, and then tentatively compensates for this channel. The transmission map will therefore be more accurate than that of the old DCP method, and the dehazing performance will be more significant. After the coarse output image is acquired, the average hue of all pixels in the whole image is calculated as an indicator which determines whether the color restoration is still needed. To reduce color cast, the direct utilization of gray world theory may exacerbate the artifacts. Therefore, the compensated gray world (CGW) theory will be used to avoid exacerbating the artifacts[11].

The DCP method is valid in the image dehazing process, and it is also reasonable for estimating the transmission map on land. The DCP-guided enhancement methods usually produce some patch artifacts for challenging underwater images, where the artifact removal becomes a crucial task. Targeting the patch artifacts, this paper combines several mechanisms to finish the artifact removal. The following is the contributions of this paper.

Adaptive classification and processing (ACP): Distinguish an underwater image into three cases: (1) Heavy attenuation of the B channel; (2) Heavy attenuation of the R channel; (3) Somewhat uniform attenuation for each channel. According to the results of the distinction, different mechanisms are applied for the transmission map estimation.

Compensated color restoration and post-processing (CCRP): Design a novel mechanism to determine whether the color restoration is needed. If the color restoration is needed, the CGW theory is utilized. In post-processing, each sub-patch is classified, and an extra filter is added to further achieve our goal.

In recent years, the research on underwater image dehazing is proliferating. LU et al[12] established a multi-scale adversarial network for underwater image recovery, which uses deep learning and DCP dehazing to improve the recovery quality. BIANCO et al[13] used the differences of RGB three-channel attenuation ratios in water body to predict the underwater scene depth and obtain a more precise estimation of the transmission map. CHIANG et al[14] used a wavelength compensation method to improve underwater images. CUI et al[15] combined the DCP and Pyramid image fusion to finally achieve the recovery and enhancement of underwater images. GALDRAN et al[16] proposed a restoration method especially for the R channel, which can well improve the color cast and visibility.

For removing various artifacts during image enhancement, MUSUNURI et al[17] proposed a hidden Markov random field method to recover the hazy images, which can reduce artifacts and make the image clear. SINGH et al[18] established a bright channel prior where a gain intervention filter is used to deal with the artifacts, and the prior can effectively reduce the computational cost. HAN et al[19] utilized a scene radiance constraint to accurately estimate the transmission map, and thus obtained an excellent performance on color restoration. Considering the low light situation, MARQUES et al proposed an inverse dehazing method that subtracts a maximum value from each pixel, turns the dark area into a bright area, and then treats the bright area as a hazy area during the dehazing process.

What we want to achieve in this paper is the removal of the patch artifact that appears in the DCP-guided enhancement, especially challenging underwater images. If we want to get a refine transmission map from the original image, the intensity attenuation of the RGB channels should be fully taken into account, and the mechanism of Ref.[6] can be used to estimate the backscattered light. By analyzing plenty of image data, HE et al[5] came to the conclusion that most non-sky areas always have a channel with a very low intensity approach to zero. For the convenience of discussion, a basic imaging model is shown as

$$P(i)=Q(i)T(i)+L[1-T(i)] \ , \tag{1}$$

where $P(i)$ is the original input image, $T(i)$ is the transmission map, and $Q(i)$ is the output image that is haze-free, and L is the backscattered light. In Eq.(1), the DCP mechanism can gradually estimate L, $T(i)$, and $Q(i)$. In the DCP-based dehazing methods, the DCP can be used as an elimination operation that makes $Q(i)$ close to 0:

$$Q^{\text{dark}}(i)\rightarrow 0. \tag{2}$$

Thus, the dark channel operations are simultaneously performed on both sides of Eq.(1), and they will make $Q(i)T(i)$ approach 0. After getting L, the original DCP method can easily obtain the transmission map approximation $\tilde{T}(i)$, which can eventually be substituted into Eq.(1) to get the desired output $Q(i)$. In the DCP method, the transmission map of the RGB channels can be expressed as

$$T(i)=1-\theta\cdot\min_{S\in\{R,G,B\}}[\min_{j\in\Omega(i)}\frac{P^S(j)}{L}], \tag{3}$$

where $\Omega(i)$ is the patch size, θ is the ratio parameter, and S is one of the RGB channels. By choosing patch sizes, different transmission maps may be obtained in a very refined manner[20]. The intermediate image is employed for the guided filtering after the transmission map has been obtained. The generated images with the aforementioned patch-by-patch procedure might have some artifacts[7,9]. In challenging image enhancement, the DCP-based method will unavoidably cause some patch artifacts. Meanwhile, the color restoration may oversaturate some areas and cause some small artifacts. The proposed method for getting rid of the patch artifacts will be demonstrated in the following section.

In this work, a coordinated underwater dark channel prior (CUDCP) method is proposed to reduce the patch artifacts, especially for challenging underwater images. Moreover, the CGW theory is used to avoid the patch artifacts that would be exacerbated by other white balance algorithms. In addition, a patch-division average filter is implemented. A single processing mechanism is difficult for the artifact removal, so this paper utilizes multiple mechanisms together to reach the goal. The CUDCP method compensates for differences in wavelength attenuation to alleviate color cast. According to earlier studies results, the physical modeling of a trichromatic underwater image can be expressed as

$$P^S(i) = Q^S(i)T^S(i) + L^S[1 - T^S(i)],\ \ S \in \{R,G,B\}, \tag{4}$$

where i is a pixel in an image, and $T^S(i) \in [0,1]$ is a transmission map to describe the fraction of light arrival, and L^S is the backscattered light. $Q^S(i)T^S(i)$ is a part of the final image during underwater imagery, and $L^S[1-T^S(i)]$ is another part of its final image from the backscattered light. To obtain a hazy-free image $Q^S(i)$, $T^S(i)$ and L^S must be estimated. The DCP method is to use the dark channel prior to get the transmission map, but it is irrational for directly applying DCP to underwater images. Due to the absorption of water for light, the underwater images after simple enhancement may also have color cast, so we also need to add some suitable operations for color restoration. Under underwater circumstances, the proposed method coordinates every channel to mitigate the defects of other DCP-based methods, particularly patch artifacts. Overall, Fig.1 illustrates the detailed flowchart of the proposed CUDCP method.

For estimating the backscattered light, a DCP-based method is straightforward by selecting the brightest pixel in an image[6]. In many actual cases, the brightest pixel may be in a white area. In this work, the DCP mechanism is extended for a more accurate estimation of backscattered light. Our CUDCP method firstly operates with the dark channel prior, and then chooses the brightest 0.1% of the pixel points, and subsequently chooses the point with the highest intensity among these selected pixel points as the backscattered light estimation. Despite the fact that this estimation might not be the brightest component of the original image, these operations will certainly make the estimation more accurate. This estimation serves as the foundation for the succeeding steps of our CUDCP method.

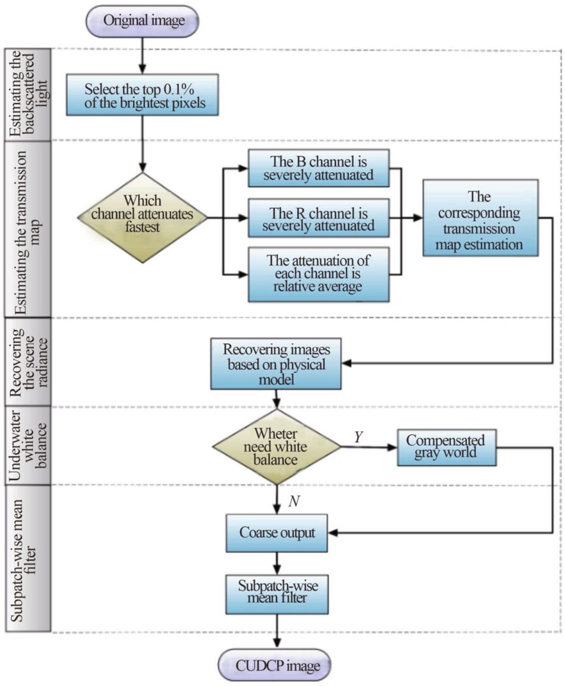


Fig.1 Flowchart of the CUDCP method

The previous subsection has obtained L^S. Furthermore, the transmission map is obtained by dividing both sides of Eq.(4) by L^S simultaneously. Due to the nature of the DCP, the intensity of a hazy-free image processed by dark channel prior will tend to be 0. As a more realistic and accurate imaging model, the trichromatic transmission map can be estimated by the following dark channel prior:

$$T^S(i) = 1 - \theta \cdot \min_{j\in\Omega(i)}[\min_{S\in\{R,G,B\}} \frac{P^S(j)}{L^S}], \tag{5}$$

where the parameter θ can make our model accurate, typically θ=0.95. The transmission map will undoubtedly be impacted by the value of the parameter $\Omega(i)$, which stands for the patch size. Fig.2 shows the enhancement results of different patch sizes, where column (a), (b), and (c) represent the enhancement results of 15×15, 9×9, and 3×3 patch sizes, respectively. A small patch size can remarkably diminish the patch artifacts, but this is at the cost of the dehazing effect. For a reasonable and fair comparison with other DCP-based methods, the patch size of 15×15 pixels is still used herein.

Ref.[10] focused on the attenuation anomaly of the R channel, and the attenuation ratio is greater than that of the green (G) and blue (B) channels, so only the G and B channels were used in the subsequent estimation of the transmission map. However, in shallow sea regions, such assumptions are not valid. Therefore, the following formula is used herein to estimate the channel-aware transmission map.

$$T^S(i)=\begin{cases} T_{\mathrm{GB}}^S(i) & \mathrm{mean}(I^{\mathrm{r}})\le\sigma \\ T_{\mathrm{RG}}^S(i) & \mathrm{mean}(I^{\mathrm{b}})\le\sigma \\ \beta\cdot T_{\mathrm{GB}}^S(i)+(1-\beta)T_{\mathrm{RG}}^S(i) & \text{otherwise} \end{cases}, \quad (6)$$

where $T_{\mathrm{GB}}^S(i)$ is the transmission map which is got by the G and B channels. By the same token, $T_{\mathrm{RG}}^S(i)$ is got by the R and G channels. σ=0.2, $\beta=[1+\mathrm{e}^{-\varepsilon(\mathrm{mean}_S(L_S)-0.5)}]^{-1}$, and ε is typically 32.

It can be seen from Eq.(6) that if the average intensity of the R channel is below the threshold σ, the R channel will be ignored when the transmission map is estimated. The same operation is performed if the average intensity of the B channel is below the threshold σ. Depending on the average intensity of the RGB channels, all underwater images can be simply divided into three types: heavy attenuation of the B channel, heavy attenuation of the R channel, and somewhat uniform attenuation for each channel. Therefore, Fig.3 displays three different attenuation diagrams respectively. The channel-aware transmission map is the basis of our method.

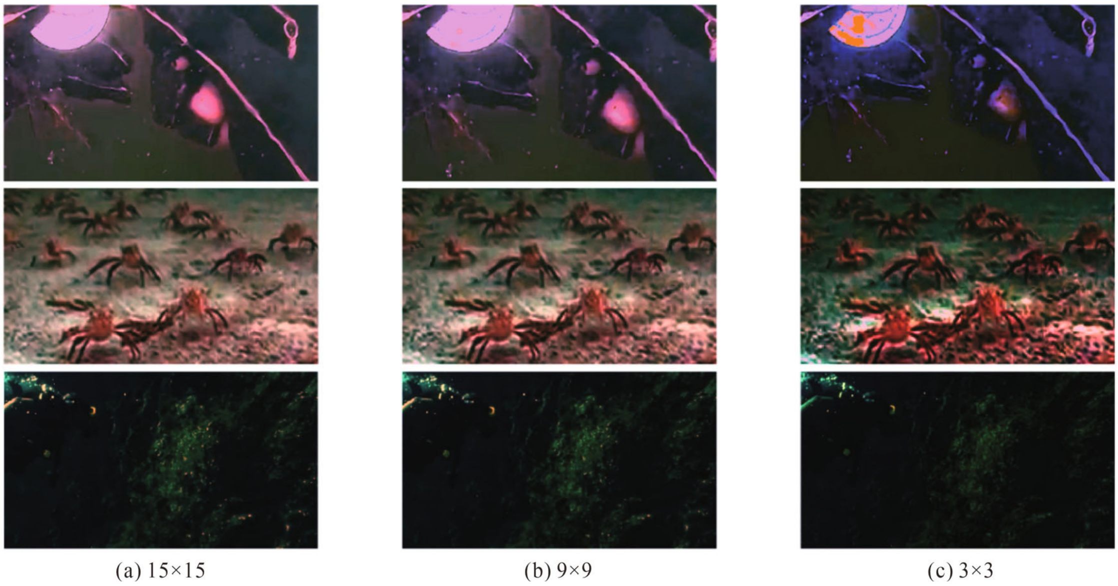


Fig.2 Processing results with different patch sizes

After obtaining the channel-aware transmission map, through Eq.(4) we can recover the scene radiance. But if the transmission map $T^S(i)$ approaches 0, the conformity term $Q^S(i)T^S(i)$ approaches 0, where noise is easily generated in the preliminary dehazed scene $Q^S(i)$. As the CUDCP method has limited the transmission map $T^S(i)$ to the lower limit T_0 as a result of this observation, some blurs are now only present in extremely dense locations. In order to recover the scene radiance $Q^S(i)$, L_S and $T^S(i)$ from $P^S(i)$ is needed. The dehazed scene is demonstrated by using the physical modeling described above along with DCP, and the scene is expressed as

$$Q^S(i)=\frac{P^S(i)-L^S}{\max(T^S(i),T_0)}+L^S,\ S\in\{R,G,B\}, \quad (7)$$

where T_0 is often set to 0.1 because the denominator shouldn't be too small. When the blur is removed, the image will appear a little bit darker because the scene brightness is often lower than the brightness of the backscattered light. Thus, the proposed method has got a coarse dehazed image, and it is far from enough by the above operations. After already considering the different absorption of waterbody for different channels, the CUDCP method can divide the underwater images into three types and adaptively process them for different types. In the next subsection, this paper will use the CGW theory to coordinate with the coarse dehazed image.

Since water affects the travel of light, the suspended substances in waterbody can cause scattering of light, and they can lead to degradation of image quality, which ultimately reduces the hue, visibility, and overall contrast of the intermediate image. So, this paper uses the white balance for further processing. Usually the gray world theory is very appropriate for white balancing underwater images. But due to the R or B channel attenuation, the direct utilization of gray world theory may result in some artifacts. By applying the CGW theory to coordinate channel intensity, our CUDCP method can effectively solve the distortion problem caused by channel differences.

To determine whether the white balance is needed, we provide the formula below

$$k=\frac{1}{MN}\sum_i(\bar{h}-h(i)), \quad (8)$$

where M and N are the height and width of the original image, $h(i)$ is the brightness at pixel position i, while k

can be thought of as a brightness indicator for the entire image, and $\overline{h}$ is created by averaging the hue values throughout the entire image. The intermediate image does not need the white balance, according to $k>\sigma$ (σ=0.2), or else, the intermediate image achieves the white balance through the CGW theory.

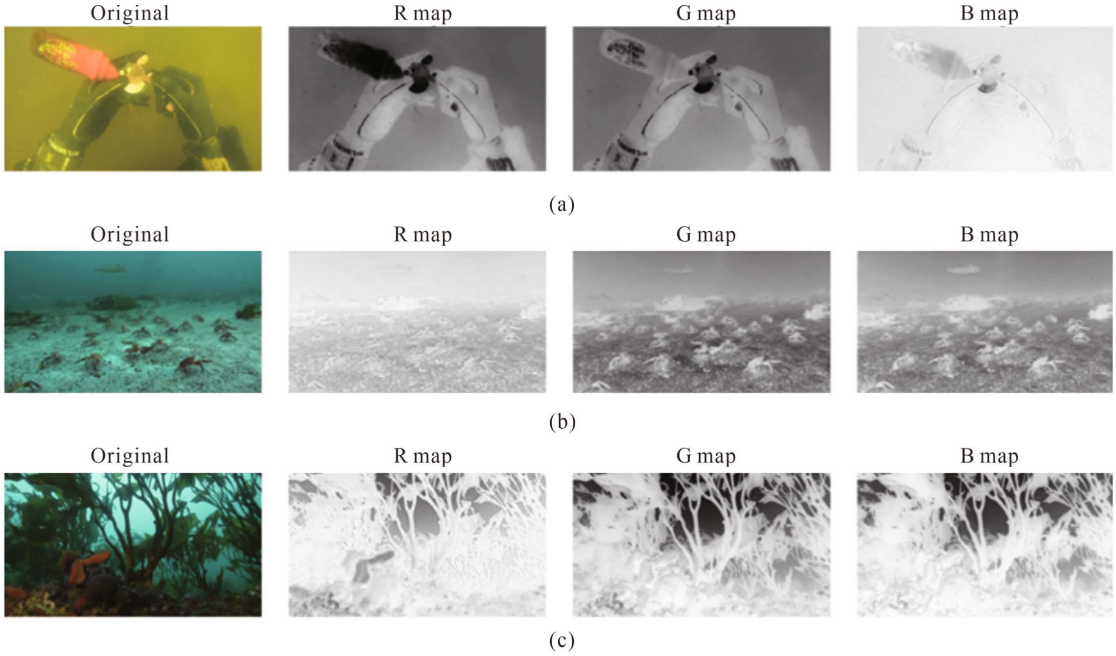


Fig.3 Diagram of attenuations for the three types: (a) Heavy attenuation of the B channel; (b) Heavy attenuation of the R channel; (c) Somewhat uniform attenuation for each channel

Based on the characteristics of DCP, the appearance of the patch artifacts is inevitable in the DCP-based results. After implementing the previous steps, an additional module will be added to further reduce patch artifacts.

Splitting an image into some sub-patches has many advantages. At the same time, the processing of a large-size image requires a lot of storage space to store image information, excellent hardware and software, and a proper method. Since the image has been divided, sub-patches can be stored for parallel processing. Different from the above patches, the sub-patches are obtained by dividing the input image. The CUDCP method must reduce the dependence on resources and increase the generalization ability, so as to reduce the memory and computing pressure of each operation.

The image will be split into sub-patches of height H and width W. Every sub-patch is marked with a number based on its index, which is represented as (0, 0), (0, 1)…, (i, j)…, (n−1, m−1). It can be seen from Fig.4, the beginning of the sub-patch at index (i, j) is the pixel point P. It is obvious that the pixel point P is obtained by the (0, 0) sub-patch which moves $i\times$*Patchwidth* pixels to the right and $j\times$*Patchheight* pixels down. By using these coordinates, the sub-patches can be recovered in order.

Since dividing the image into sub-patches, the CUDCP method uses a variance threshold in conjunction with the Sobel operator to distinguish the offset sub-patches to be divided into flat and textured sub-patch.

$$t=\frac{1}{64}\sum_{x=0}^{7}\sum_{y=0}^{7}f(y,x),$$

$$V_f=\sum_{x=0}^{7}\sum_{y=0}^{7}\lambda(|f(x,y)-t|),$$

$$\lambda(i)=\begin{cases}1, i\geq\xi\\0, i<\xi\end{cases}, \tag{9}$$

where V_f represents the pixel number of the texture sub-patch. The value of V_f can be used to determine whether the patch is flat or not. Here, each image is divided into 8×8 pixels sub-patches, and ξ is empirically set to 30. However, the variance threshold is for relatively independent sub-patch internal operations. The individual variance threshold leads to significant differences between patches, and this visual discontinuity presents itself in the form of patch artifacts. We can lessen the impact of this problem by including the Sobel operator. The Sobel operator employs a 3×3 template and completely considers the relationship between the processed pixel and the adjacent pixels. So, the proposed

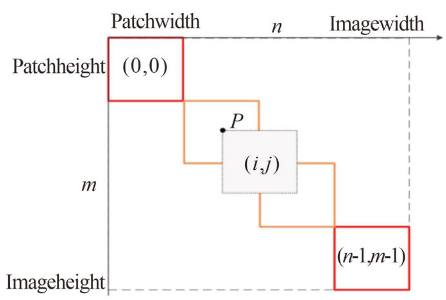


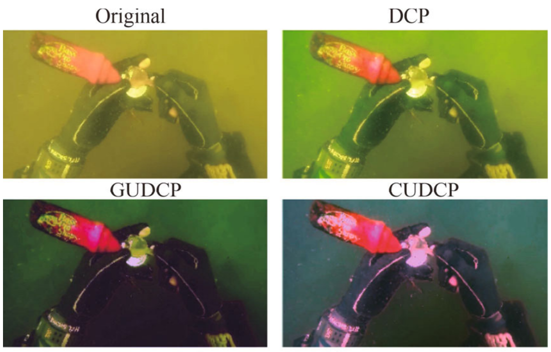
Fig.4 Splitting of sub-patches

CUDCP method applies the Sobel operator to all outermost points of the circle and the variance threshold to the remaining pixels. The CUDCP method can decide how the Sobel operator and the variance threshold should be used for the final sum calculation based on the number of pixels.

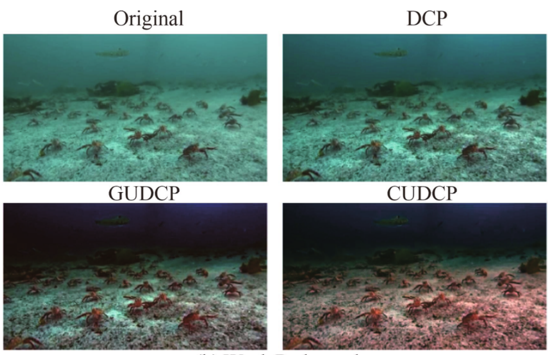
Because the mean filtering is easy to operate with obvious effect, it is an effective solution to use the mean filtering mechanism to adaptively reduce the patch artifacts. The class-adaptive mean filtering is performed according to sub-patch classification. The flat sub-patch is given a relatively powerful filter strength treatment, while the texture sub-patch receives a relatively weak filter strength treatment. Finally, the filtered offset sub-patches are combined to obtain the final image.

This paper compares the proposed CUDCP method with several state-of-the-art DCP-based methods, i.e., DCP[5], VDCP[10], and GUDCP[9]. For these methods, we respectively test and analyze their enhancement effects on two typical datasets: a challenging underwater image enhancement benchmark (CUIEB) dataset[1] and a real-world underwater image (U45) dataset[21]. Because each dataset does not contain any reference image, the non-reference qualitative and quantitative results are comprehensively presented on each dataset.

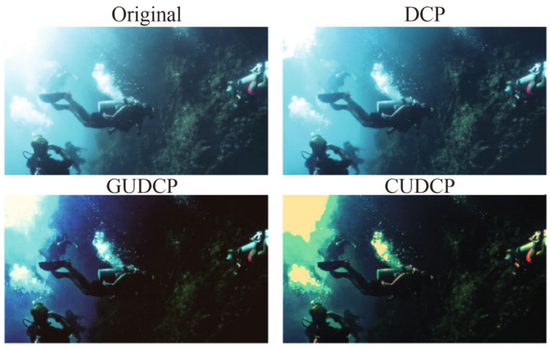
The final outcomes in three cases are shown in Fig.5. Fig.5(a) is the case where the B channel intensity is below a threshold, and the blue light attenuates quickly. Fig.5(b) shows the processing results when the R channel intensity is comparatively low. Fig.5(c) is the third attenuation case. Different operations are used in the three cases compared to the current DCP-based methods, which makes our CUDCP method more effective.



(a) Weak B channel



(b) Weak R channel



(c) Attenuation average

Fig.5 Final outcomes in three cases

Based on the underwater DCP mechanism, this paper proposes the channel-aware transmission map estimation which is suitable for challenging underwater scenes. Based on the k value from Eq.(8), an indicator can determine whether the color correction with white balance is necessary. The white balance is utilized to increase the intensity coordination of the R or B channel. For obtaining a better performance on color restoration, the CGW theory is implemented. Finally, the additional module can be used to further process patch artifacts to achieve the desired result. The patch artifacts may still appear in the final result, but they will be greatly reduced and removed after the above operations.

As we can see in Fig.6, compared with the original DCP method, DCP+CCRP can improve the color cast very well, while DCP+ACP can make the image clearer. But both CCRP and ACP have other disadvantages when being used alone. After combining the two functions, it can be seen that the proposed CUDCP method is obviously better than both of them when used alone.

For those compensated or non-compensated images, Fig.7 shows the visual effects of artifact removal. The image shows that if the gray world algorithm is used directly, it will cause artifacts to appear in some areas, but after using the CGW theory, some of the negative effects of the DCP-based method can be well mitigated. More importantly, the details in Fig.7 show that the CGW theory can successfully remove artifacts caused by the gray world theory. Further, Fig.8 illustrates the subjective quality of different enhanced images by implementing the DCP, VDCP, GUDCP, and CUDCP methods.

The underwater image quality measure (UIQM), which is based on early material, is frequently used to determine the non-reference objective quality score of an underwater image[1,2]. As seen in Tab.1, based on the CUIEB dataset, the enhanced images of our CUDCP method have higher average UIQM scores when compared with the original images and those of the VDCP method, despite the benefit being minimal compared to the GUDCP method. For our CUDCP method, the patch size of 15×15 is more effective than the 3×3, and the visual effects of the final images can be significantly improved. In addition to UIQM, the computational cost is also one important indicator for evaluating different algorithms. In Tab.2, we provide the computational cost of each method on the CUIEB dataset. It can be found that the computational cost of CUDCP is slightly higher than DCP and lower than GUDCP, while the computational cost of VDCP is the lowest.

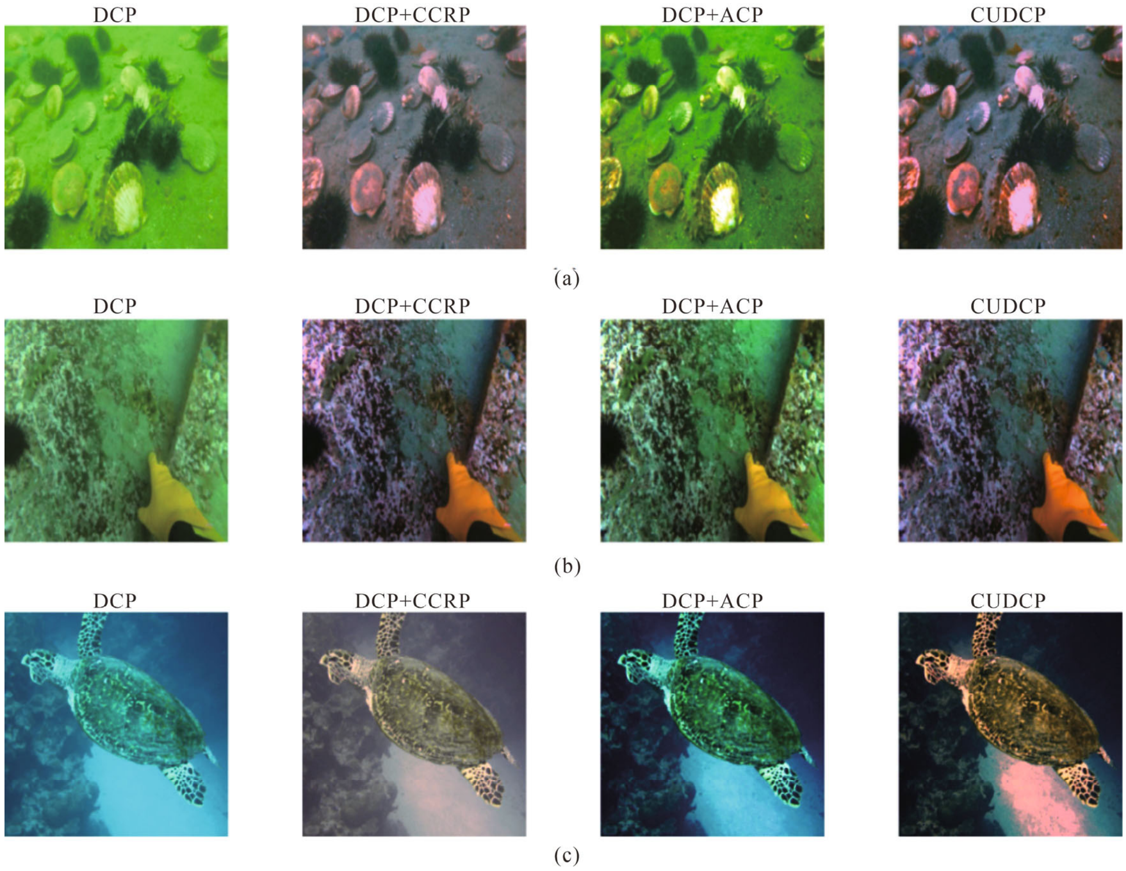


Fig.6 Three sets of images represented by (a), (b) and (c), with each set of images processed by DCP, DCP+CCRP, DCP+ACP, and CUDCP respectively

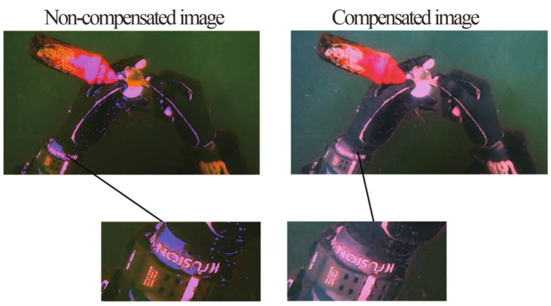


Fig.7 Visual effects of artifact removal

Tab.1 Average UIQM scores under different patch sizes on the CUIEB and U45 datasets

Patch size	UIQM scores of each method on the CUIEB			
	Original	VDCP	GUDCP	CUDCP
15×15	0.015 8	0.488 3	2.148 0	2.274 8
3×3	0.015 8	0.488 3	1.957 5	1.931 6
Patch size	UIQM scores of each method on the U45			
	Original	VDCP	GUDCP	CUDCP
15×15	2.061 2	0.500 4	4.537 5	5.095 8
3×3	2.061 2	0.500 4	4.476 5	5.021 4

Tab.2 Average computational cost under different patch sizes on the CUIEB and U45 datasets (Unit: second)

Patch size	Computational cost of each method on the CUIEB			
	DCP	VDCP	GUDCP	CUDCP
15×15	87.493 8	17.395 8	97.567 5	88.618 8
3×3	54.435 9	11.641 1	59.480 4	54.786 1
Patch size	Computational cost of each method on the U45			
	DCP	VDCP	GUDCP	CUDCP
15×15	5.602 6	0.647 2	5.867 8	5.714 1
3×3	4.316 3	0.717 8	4.588 8	4.398 9

On the U45 dataset, it can be found from Tab.1 that although the original image quality of U45 is far better than that of CUIEB, the evaluation score of CUDCP in terms of UIQM is still higher than that of GUDCP and VDCP. In terms of computational cost, only a small increase is needed to obtain better processing results.

Overall, the proposed CUDCP method has got good results in the subjective quality we focus on, and it also is superior to the GUDCP and VDCP methods in the objective UIQM evaluation scores. Therefore, both subjective and objective effects of the proposed method are competitive, while its computational cost is acceptable.

Based on the dark channel prior, this paper proposes an effective enhancement method which jointly coordinates with the backscattered light estimation, the channel-aware transmission map estimation, and the white balance for robust restoration of underwater images. Compared with some recent DCP-based methods, our CUDCP method fully considers the attenuation of the RGB channels to obtain a more accurate transmission map and implement a more suitable white balance, and finally adds a patch-division average filter to further finish the artifact removal. Moreover, the experimental data can show that the CUDCP method can significantly optimize the visual results, and maintain competitive objective quality with an acceptable computational cost.

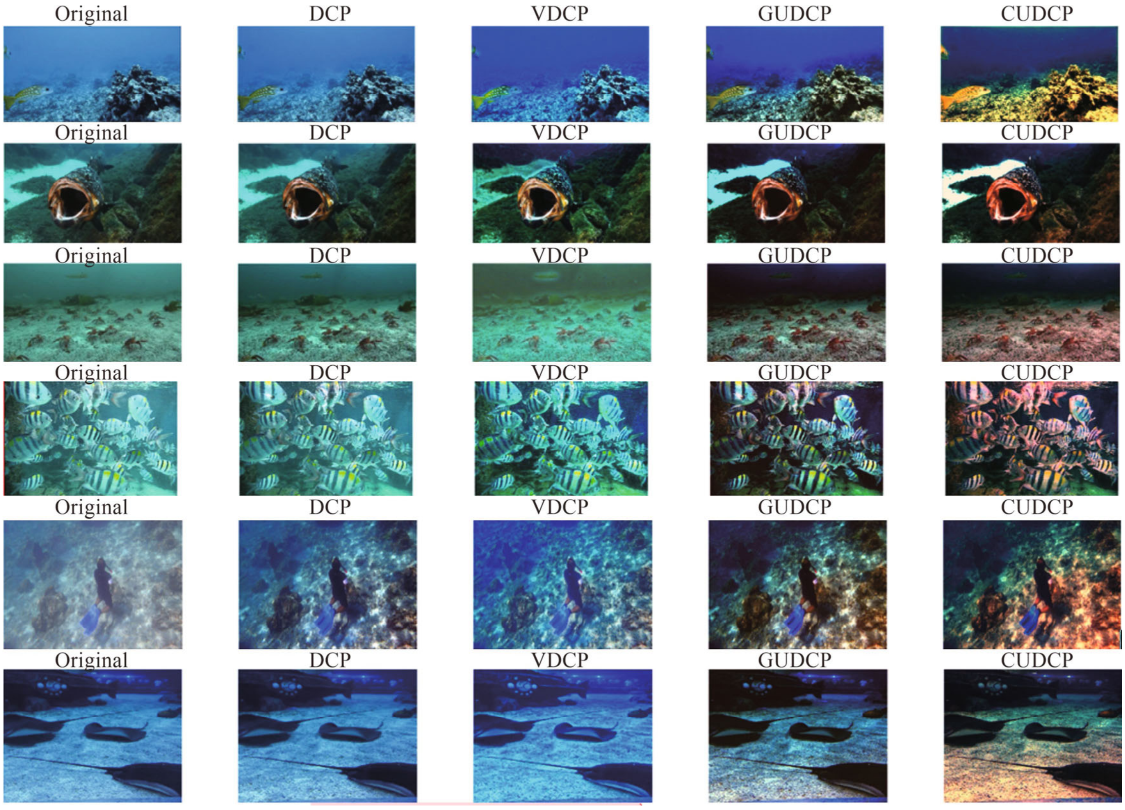


Fig.8 Enhancement results of different methods

Ethics declarations

Conflicts of interest

The authors declare no conflict of interest.

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