Chapter 4

Comparison, Evaluation and Analysis

In this chapter, the proposed underwater objects visibility enhancement method is compared to some state-of-art methods, which are evaluated by the images collected from representational underwater test images and different metrics are utilized to compare the restoration performances of these methods.

4.1 Measurements of Underwater Imaging Performance

4.1.1 Basic Evaluation Index for Underwater Imaging Performance

Expect for the subjective assessment, this subsection introduces several basic underwater image quality metrics to evaluate and analyze the performance of different underwater imaging methods, including gray average, standard deviation, average gradient, RGB color space mapping and etc.

The mean value and standard deviation are the basic and wide evaluations to measure the quality of images, which are able to reflect the intensity and contrast information of images well. Generally, gray average value of an image reflects the integral intensity, and higher the gray average is, higher the intensity is, while standard deviation of an image reflects the high frequency component of an image, which is related to the image contrast, higher the standard deviation is, higher the contrast is as well as greater color information. Meanwhile, Jobson et al. [26] indicate that an image shows good integral quality performance when its gray average between 100 and 200 and its standard deviation between 35 and 80 after they analyzed and statistic a large amount of images,

$$Mean = \frac{1}{M \cdot N} \cdot \sum_{i=1}^{M} \sum_{j=1}^{N} I(i,j) \tag{4-1}$$

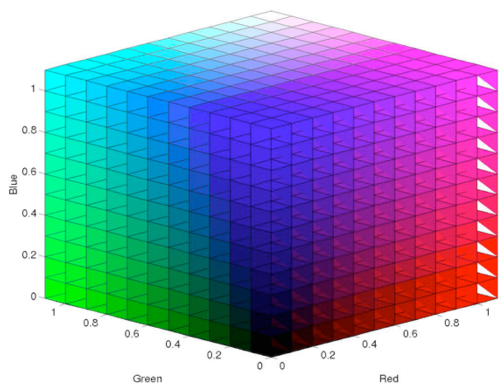
$$\sigma^2 = \frac{1}{M \cdot N} \cdot \sum_{x=1}^{M} \sum_{y=1}^{N} \{I(x,y) - Mean\}^2 \tag{4-2}$$

where $Mean$ is the gray average value of the image and σ^2 is the corresponding standard deviation. However, the average gradient reflects the velocity of the changes of minor details in the image, it can represent the features of texture transform and the degree of clearness well, and its definition is,

$$\bar{g} = \frac{1}{M \cdot N} \cdot \sum_{x=1}^{M} \sum_{y=1}^{N} \sqrt{\frac{[I(x,y) - I(x+1,y)]^2 + [I(x,y) - I(x,y+1)]^2}{2}} \tag{4-3}$$

$\bar{g}$ represents the average gradient and $M \cdot N$ stands for the number of pixels in the image, and each of them represents the size of image.

Besides, three dimensional RGB color space is able to represent all the 8-bits color within its cubic space. As shown in the Figure 4.1, each coordinate axis represents a color, i.e., red, green and blue, while it also includes the intensity of the pixels. In the RGB color space, an image with good dynamic compression range is more likely to map as much space as possible. For distorted images such as low illumination image or color casting image, their mapping results are gathered in some corners of RGB color space. For instance, the underwater image who suffers from heavy color casting and shows greenish, its mapping result is gathered in the left corner in the color space. Thus, RGB color space is utilized to analyze the integral dynamic compression range.



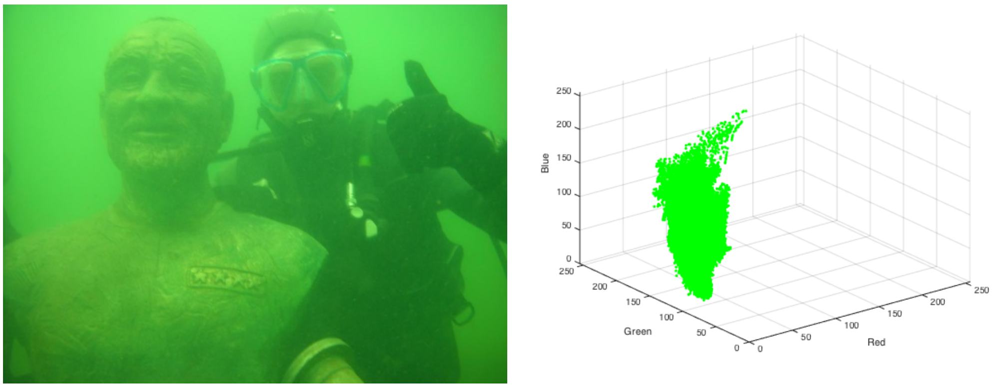


Figure 4.1, RGB color space model and an example of image mapping in the space

Since underwater imaging often plays a role of pre-processing for the certain image processing such as image decomposition, pattern recognition, visual tracking and so forth. The restored scenes and objects in the image or video needs to have a clear texture and details. Thus, we introduce the Sobel operator to detect the edges of restored images and calculate the score of the edges, where Sobel operator is shown below:

$$X_{direction} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}, \quad Y_{direction} = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \tag{4-4}$$

where $X_{direction}$ is used to detect the edges in the vertical direction and $Y_{direction}$ is used to detect the edges in the horizontal direction.

Figure 4-2, an example of edges detection of restored image

However, these basic measurements can not give a comprehensive evaluation of underwater imaging performance, since underwater image suffers various degradations and each of them has their own features, the measurements mentioned above can not cover the whole parts. In general, underwater scenes and objects suffer from color fading, sharpness attenuation and contrast degradation, thus, in order to evaluate the performance of underwater imaging well, we also need to compare these parts of restored images. So we introduce the underwater image quality metrics measurement to bring a comprehensive evaluation, which will be discussed in the next subsection.

4.1.2 Underwater Image Quality Metrics

In this subsection, we introduce an efficient underwater image quality measurement, UIQM, which is composed of three independent measurements, underwater image colorfulness measure (UICM), underwater image sharpness measure (UISM), underwater image contrast measure (UIConM) [27].

(1) Underwater Image Colorfulness Measure

Most of underwater images are degraded by color casting, and growth with depth increases, while different colors show various attenuating ratio. Generally, red component is disappeared firstly because of the shortest wavelength, while blue and green components attenuate slowly, so underwater scenes are often demonstrated to be bluish or greenish. Moreover, limited lighting conditions also causes severe color desaturation in underwater images. In order to measure the performance of color correction performance, the UICM is utilized to evaluate the performance of underwater image enhancement algorithms, and the Red-Green (RG) and Yellow-Blue (YB) color components are used:

$$RG = R - G \tag{4-5}$$

$$YB = \frac{R+G}{2} - B \tag{4-6}$$

Considering that underwater image often suffers heavy noise, instead of regular statistical values, the asymmetric alpha-trimmed statistical values [28] are used for measuring underwater image colorfulness,

$$\mu_{RG} = \frac{1}{N-T_L-T_R} \sum_{x=T_L}^{N-T_R} Intensity_{RG}(x) \tag{4-7}$$

where N is the total number of pixels in the RG component and and all pixels of the image are sorted such that $x_1 < x_2 < \cdots < x_N$, $T_L = \alpha_L \cdot N$ and $T_R = \alpha_R \cdot N$ are the number of smallest and greatest pixel values to be truncated or discarded from the sorted sequence $x_1 < x_2 < \cdots < x_N$. The first-order statistic mean value μ_{RG} represents chrominance intensity, and the average value that is closer to zero in the RG-YB opponent color component implies a better white balance, which means none of the colors are dominant. Further, the second-order statistic variance is defined by:

$$\sigma_{RG}^2 = \frac{1}{N} \cdot \sum_{x=1}^{N} (Intensity_{RG}(x) - \mu_{RG})^2 \qquad (4\text{-}8)$$

σ_{RG}^2 represents the pixel activity and a greater variance corresponds to a higher dynamic range. What's more, the first and second order statistic information μ_{YB} and σ_{YB}^2 of the yellow-blue component can be computing in the similar way.

The overall colorfulness coefficient metric which is used for measuring underwater image colorfulness is able to demonstrated in

$$UICM = -0.0268 \cdot \sqrt[2]{\mu_{RG}^2 + \mu_{YB}^2} + 0.1586 \cdot \sqrt[2]{\sigma_{RG}^2 + \sigma_{YB}^2} \qquad (4\text{-}9)$$

$UICM = -0.575$ $\qquad$ $UICM = 4.843$

Figure 4.3, UICM example of original image and restored image

Table 4.1, statistic values of UICM for diver image

	μ_{RG}	μ_{YB}	σ_{RG}	σ_{YB}	*UICM*
LEFT	-1.067	61.696	13.194	11.045	-0.575
RIGHT	-1.432	5.03	21.560	25.770	4.843

As shown in the Figure 4-3 and Table 4-1, the $UICM$ of restored image is much greater than original image.

(2) Underwater Image Sharpness Measure

Sharpness reflects the details and edges of an image, and fine captured images are likely to show better sharpness. However, for images captured under the water, severe blurring and distortion occur due to backscatter and absorption. In order to measure the sharpness, the Sobel operator is first applied on each color component to generate the edge maps. Then the obtained edge maps are multiplied to original color component to calculate the gray-scale edge maps. By doing this more efficient, the enhancement measure estimation (EME) measure [27] is utilized to measure the sharpness

$$EME = \frac{2}{m \cdot n} \cdot \sum_{k=1}^{m} \sum_{l=1}^{n} log\left(\frac{I_{max,k,l}}{I_{min,k,l}}\right) \tag{4-10}$$

where the image is divided into $m \cdot n$ blocks, and obtain the maximal and minimal pixel values in each block, $I_{max,k,l}/I_{min,k,l}$ indicates the relative contrast ratio within each block. Then the underwater image sharpness measure (UISM) can be written as:

$$UISM = \sum_{c=1}^{3} \lambda_c \cdot EME(grayscale\ edge_c) \tag{4-11}$$

where λ_c is the weight coefficient of each color component, normally, $\lambda_R = 0.299$, $\lambda_G = 0.587$, $\lambda_B = 0.114$ for red, green and blue color channels.

$UISM = 6.683$ $UISM = 7.654$

Figure 4.4, UISM example of original image and restored image. Left: underwater backscatter image, right: descattered image by proposed method, it seems that original image suffers heavier blurring effect.

(3) Underwater Image Contrast Measure

Contrast is the attribute related to underwater visual performance. For underwater images, contrast degradation is usually caused by backscattering. The contrast performance can be measured by the logAMEE measurement, and it is defined by:

$$logAMEE = \frac{1}{m \cdot n} \cdot \sum_{k=1}^{m} \sum_{l=1}^{n} \frac{I_{max,k,l} - I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}} \cdot log\left(\frac{I_{max,k,l} - I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}}\right) \quad (4\text{-}12)$$

and the underwater image contrast measure can be written as:

$$UIConM = logAMEE(Intensity) \quad (4\text{-}13)$$

$UIConM = 0.651$ $UIConM = 2.234$

Figure 4.5, UIConM example of original image and restored image. Left: original underwater image, right: contrast enhanced image by proposed method, which shows greater improvement of contrast.

(4) Underwater Image Quality Measure

It has been demonstrated that underwater images can be modeled as linear superposition of absorbed and scattered components [27]. Meanwhile, the water absorption and backscatter by dusk-like particles are able to cause color casting, sharpness attenuation and contrast degradation. Therefore, it is reasonable to use the linear model for generating the overall underwater image quality measure, thus the underwater image quality measure (UIQM) is given by:

$$UIQM = \alpha \cdot UICM + \beta \cdot UISM + \gamma \cdot UIConM \quad (4\text{-}14)$$

where the colorfulness, sharpness and contrast measure are combined together through the linear function designed above, and α, β, and γ are the weight coefficients to control the importance of each measure and balance their values. Generally, these parameters are set to be $\alpha = 0.0282$, $\beta = 0.2953$ and $\gamma = 3.5753$.

4.2 Experiment Results and Evaluations

In this subsection, we use the measurements mentioned above to evaluate the performance of proposed underwater objects visibility enhancing method as well as comparison to the state-of-art methods. For this case, we compare the performance of our method to several state-of-art methods in recent years, where most of them also achieves excellent performance for the underwater imaging issue. Generally, we introduce the methods proposed by Ancuti et al. [16], Galdran et al. [5], Fu et al. [17], He et al. [4], Getreuer et al. [11] and etc.

4.2.1 Basic Evaluation Measurements among Different Methods

Images captured in the different underwater environments often show various attenuation and degradation degree, which causes that an underwater imaging method may performs well for several certain underwater environment conditions, but weak for other conditions. We choose a set of images for evaluation.

Diver Image Open Scene Image Fish Image

Figure 4.6, The set of images chosen to evaluation and comparison

We first process (a) image shown in the Figure 4-6 by several state-of-art methods and the result is shown below.

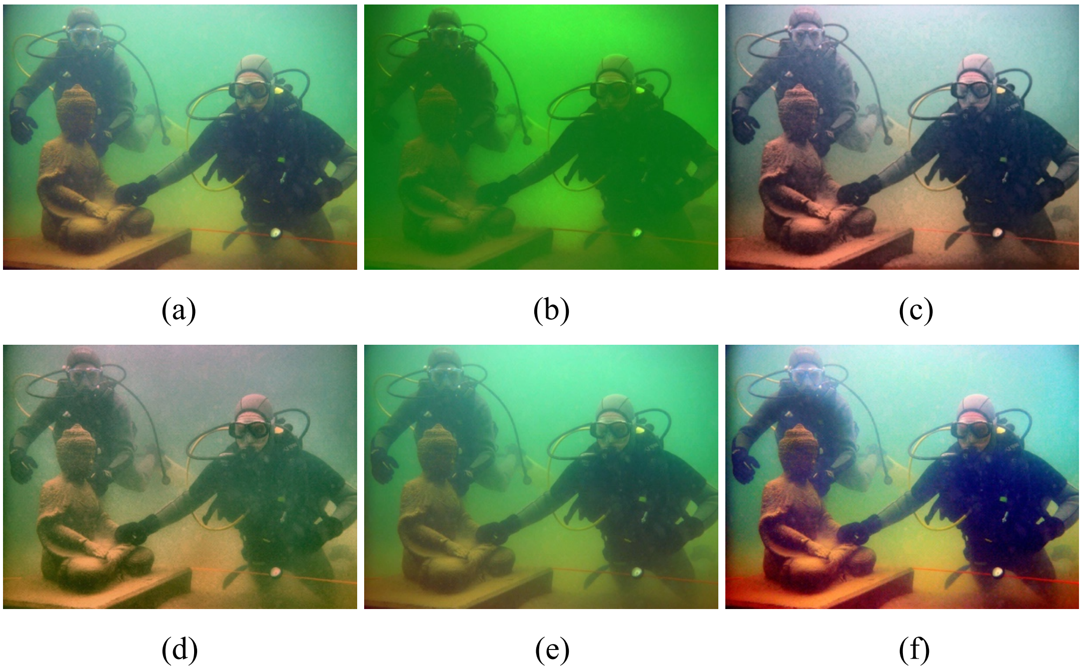


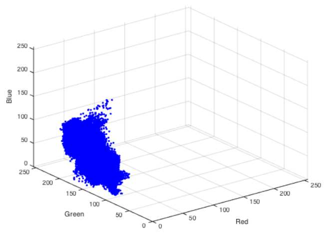
Figure 4.7, Results on the diver image via different methods. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

We see that on the diver image, the histogram equalization (HE) method fails to correct and enhance the visibility of degraded image, while ACE method shows good color correction as well as proper contrast enhancement, the restored results generated by other three methods also achieve color correction and contrast enhancement, their mean value, standard deviation and average gradient are greatly improved, as shown in the table 4.1. Expect the highest mean value, standard deviation and average gradient, the objective visual performance of the result obtained by our method are better than other methods.

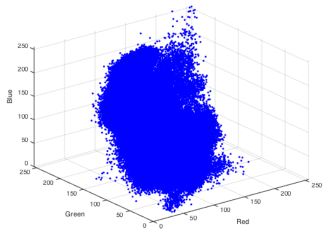
Table 4.2, Basic visibility recovery coefficient of diver image

	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*
Mean Value	88.7	117.3	70.3	114.0	103.9	104.2	**124.4**
Standard Deviation	21.00	45.63	25.94	61.76	38.81	42.87	**80.33**
Average Gradient	1.31	4.90	1.91	3.93	3.94	2.88	**5.89**

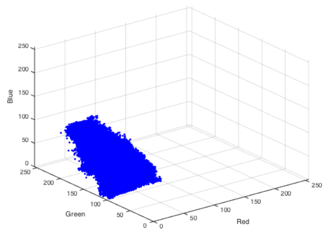
Moreover, we can see from the RGB color space of the original images and restored results that all the pixels of original image maps into the RGB color space are gathered in the left corner, where is large green value and small blue and red value, and other methods achieve more or less stretch of the pixel mapping results. It is obvious that the mapping result of our method is best and it maps the largest area in the RGB color space, which means it has the best integral dynamic compression range. However, many mapping pixels of our method is mapped onto the boundary, i.e., dark region (pixel value is 0) and brightest region (pixel value is 255), it indicates that there is information loss of our method.



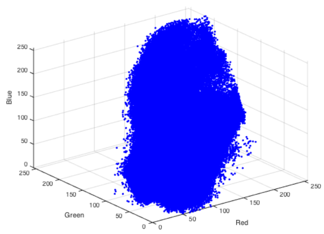
(Original)



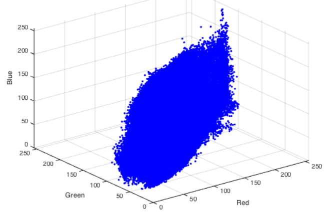
(a)



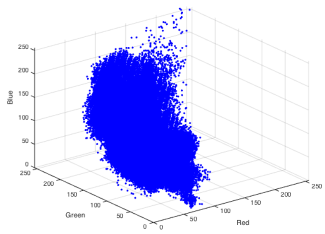
(b)



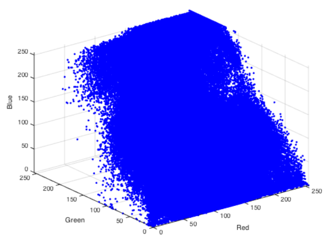
(c)



(d)



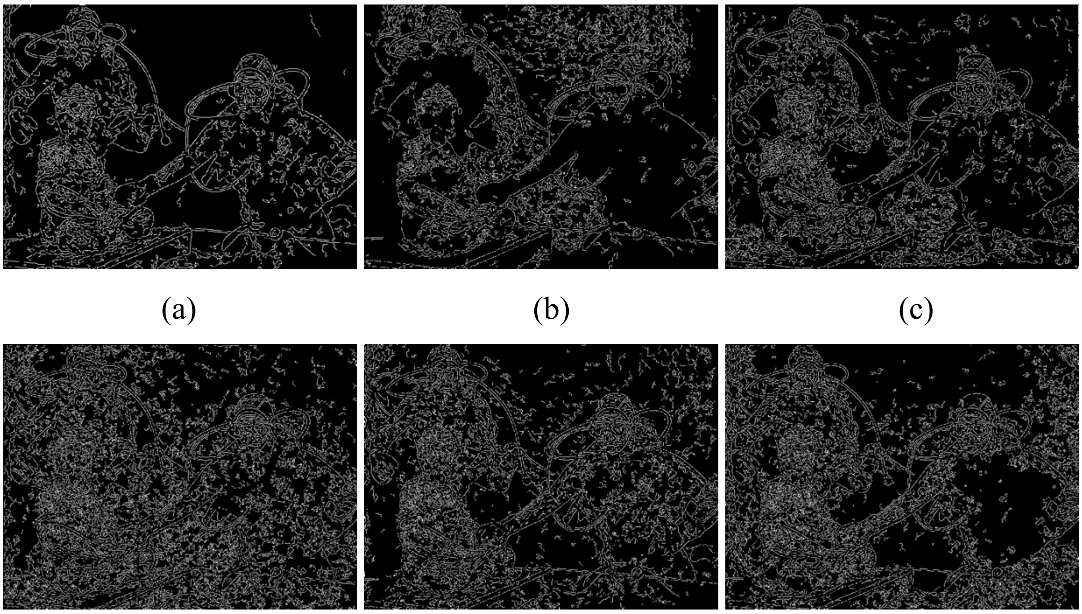
(e)



(f)

Figure 4.8, RGB color space mapping of different restoration methods on diver image. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

As we mentioned before that underwater imaging often plays a role of pre-processing for the certain image processing such as image decomposition, pattern recognition, visual tracking and so forth. The texture and details are important for images and they are also the evaluation standards to measure the performance of an image, so we will compare the edge information of these restored results.



(a) (b) (c)

(d) (e) (f)

Figure 4.9, Edge information of different restoration methods on diver image. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

Figure 4.9 gives the edge information of different restoration results, Ancuti et al. [16] preserves the edges best, following by the Galdran et al. [5]. Due to the information loss effects, the edge of our restoration result does not outperform the two results, but still better than other three methods.

For this diver image, our method achieves the integrally best performance, although it seems that some information loss exists. Actually, our method not only achieves excellent performance for heavy color casting images, like diver image above, but also performs well on images captured in different underwater environments. For the open scene image, the restoration results are shown below.

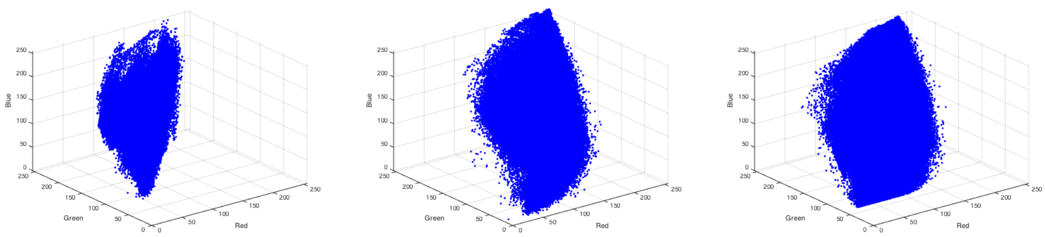
(a) (b) (c)

(d) (e) (f)

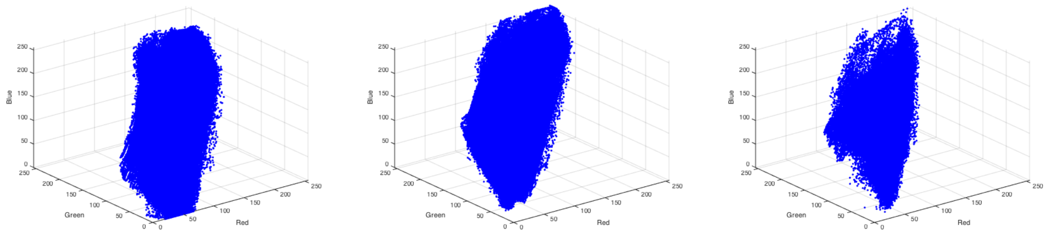
Figure 4.10, Results on the open scene image via different methods. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

Table 4.3, Basic visibility recovery coefficient of open scene image

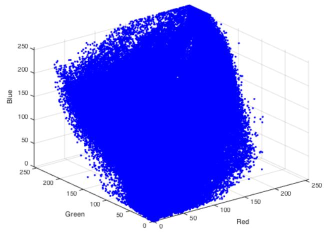
	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*
Mean Value	116.1	**125.2**	111.1	101.3	121.1	110.3	108.9
Standard Deviation	32.88	53.48	55.91	62.87	50.32	38.12	**76.31**
Average Gradient	5.64	10.35	10.70	9.64	11.56	6.65	**12.79**



(Original) (a) (b)

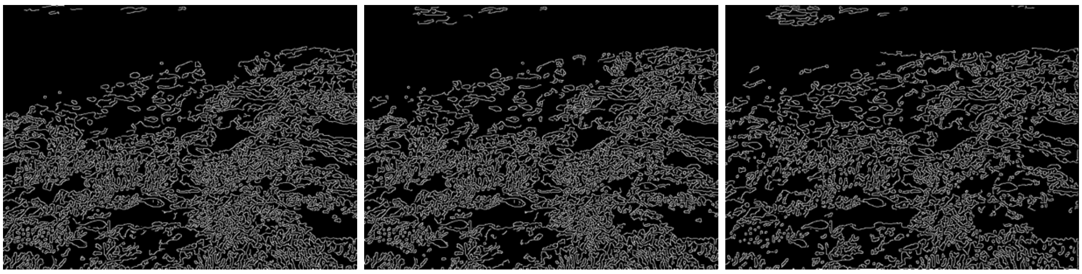


(c) (d) (e)

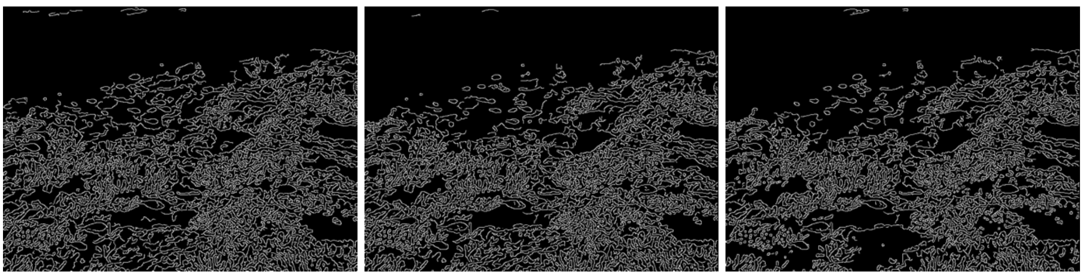


(f)

Figure 4.11, RGB color space mapping results on open scene image. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.



(a) (b) (c)



(d) (e) (f)

Figure 4.12, Edge information of different restoration methods on open scene image. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

Although the ACE method outperforms our method in mean value, our method still performs best among all these methods, which has excellent visual performance as well as good RGB color space mapping and higher contrast degrees, but its edge information does not achieve well because of the information loss. Among these methods, we can see that Fu et al. over-enhancing the distorted image, which causes severe color distortion and noise amplification, thus the integral performance of enhanced image is worse. Galdran et al. solves the effect of color casting and contrast degradation to some degree, but it is not enough, the results still tends to be greenish, while Ancuti et al. gets the good result, not only correcting the color casting but also enhancing the contrast. For histogram equalization method as well as ACE method, which are image processing methods, aim to normalize and regularize the histogram of an image and achieve the contrast enhancement and color correction. By comparison, although the histogram equalization method fails to solve the issue of diver image, it achieves good result for the open scene image, which indicates that this method is not suitable for dense color casting and heavy hazy situation. But for ACE method, it performs well in both of two test images. Moreover, another image enhancement results are shown.

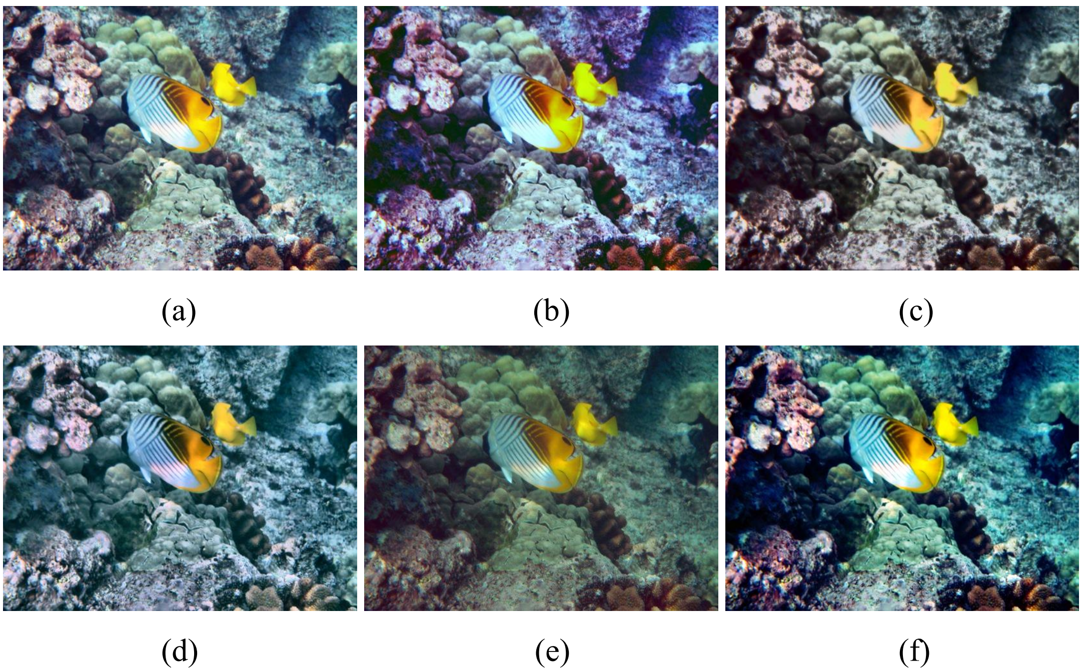
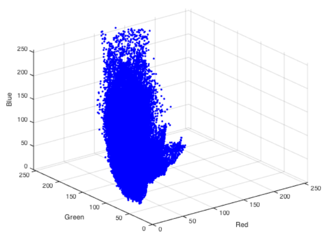


Figure 4.13, Results on the fish image via different methods. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed

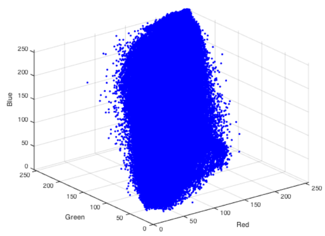
method.

Table 4.4, Basic visibility recovery coefficient of fish image

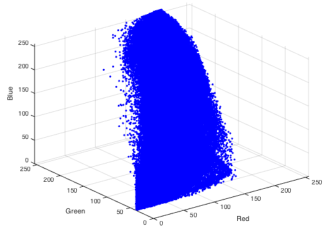
	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*
Mean Value	82.6	**118.2**	113.2	96.8	107.1	82.6	89.4
Standard Deviation	32.31	59.55	65.51	62.90	57.35	37.46	**64.90**
Average Gradient	5.86	11.83	**12.44**	10.46	13.01	6.76	12.29



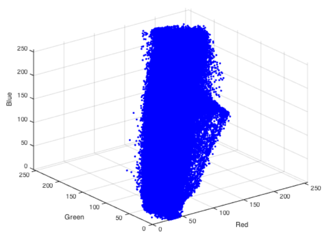
(Original)



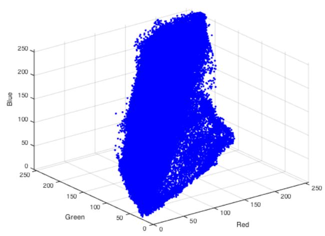
(a)



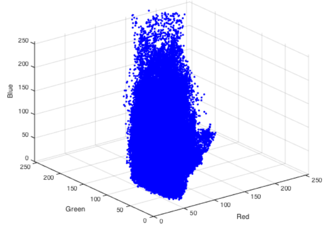
(b)



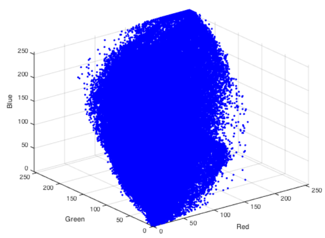
(c)



(d)

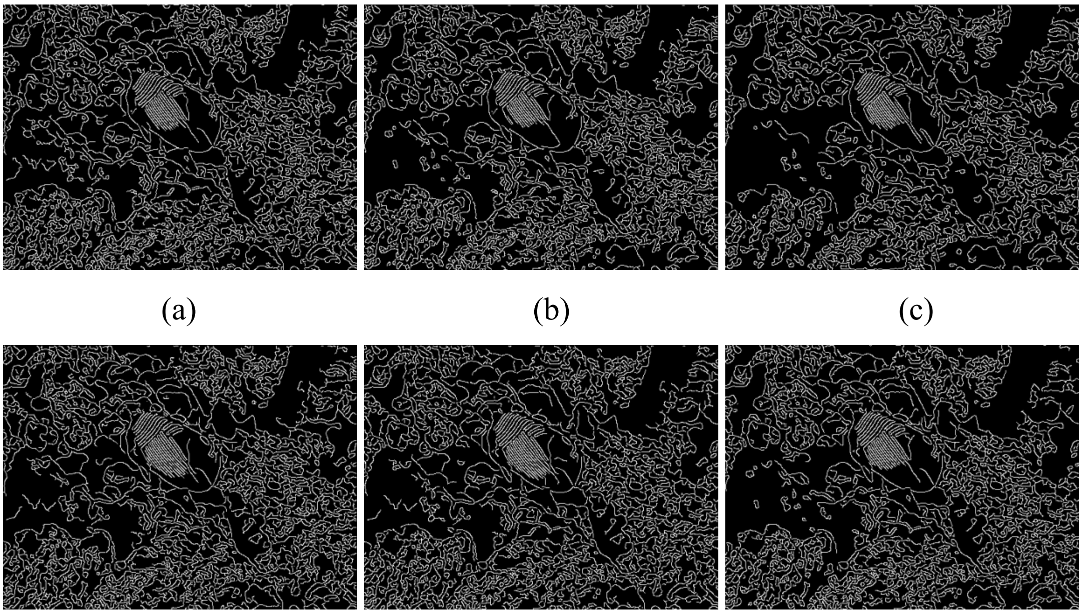


(e)



(f)

Figure 4.14, RGB color space mapping results on fish image. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.



(a) (b) (c)

(d) (e) (f)

Figure 4.15, Edge information of different restoration methods on fish image. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

4.2.2 UIQM Measurement among Different Methods

Although the measurements used in subsection 4.2.1 gives us some performance information of restoration performance of different methods, these measurements are not used to evaluate the underwater imaging issue, so they can only give some certain parts of the comparing results. In order to overcome the drawbacks of traditional image measurements and evaluate the performance of underwater imaging well, we introduce the underwater image quality metrics (UIQM) [27] measurement to give a comprehensive evaluation. Similarly, we also choose a set of distorted underwater images to be corrected and enhanced by different methods and then utilize the underwater image quality metrics measurement to evaluate their performance. These original images are shown below.

Diver Image (2) Shoal Image Shoal Image (2)

Figure 4.16, Another set of images chosen to evaluation and comparison

Firstly, we show the restoration results of different underwater imaging methods, as shown in Figure 4-17, it is obvious that several results perform well for this diver image, the subjective visual performance improves after executing the restoration expect for the histogram equalization (HE) method, which shows poor ability for stretching color dynamic range of original image. Our method achieves great result but the boundary effect tends to be worse than other method, i.e., relatively high information loss in the boundary regions compare to other results.

(a) (b) (c)

(d) (e) (f)

Figure 4.17, Results on the diver image (2) via different methods. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

Despite the subjective visual evaluation method, we also introduce the underwater image quality metrics to evaluate the performance of underwater imaging methods well. The underwater image quality metrics is composed by colorfulness metric, sharpness metric and contrast metric, where colorfulness metric is utilized to measure the color correction performance, sharpness plays a role of reflecting textures and edges of the restored image and contrast metric is used to measure the contrast of restored image.

Since human eyes are more sensitive to low frequency component of an image, where low frequency component reflects the intensity and color of the image, and can not show the small change of high frequency component, which reflects the details and texture information of the image. Based on this case, we find that the visual performance of images has the most influence for determining the image quality, and color casting contributes the most effects to visual performance. So we first analyze the color correction performance of these methods by underwater image colorfulness metric (UICM). As shown in the table 4-5, we compare the mean value and standard deviation of Red-Green (RG) channel and Yellow-Blue (YB) channel, followed by the UICM values. We have mentioned before that an image with good color performance when the μ_{RG} and μ_{YB} are both near to zero, while the contrast is measured by σ_{RG} and σ_{YB}, who should be as large as possible. The μ_{RG} and μ_{YB} of original image is large (-106.74, 61.70) due to the color casting caused by light absorption, where red component attenuates fastest and blue component is absorbed and backscattered by dusk-like particles in this specific water environment, while σ_{RG} and σ_{YB} stay at a low level because of haze. After restoration, Fu et al. achieves the best results in correct the μ_{RG} and μ_{YB}, which is -0.99 and -1.09 separately. They are close to zero. Galdran et al. generates the largest σ_{RG}, while our method gets the highest σ_{YB}. In sum, our method obtains the highest score after computing the UICM value, which means that the proposed method performs best among these algorithms under this measurement standard.

Table 4.5, underwater image colorfulness metric (UICM) results of diver image (2)

	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*

μ_{RG}	-106.74	-20.89	-66.48	**-0.99**	-21.90	-45.83	-20.35
μ_{YB}	61.70	5.59	44.56	**-1.09**	15.21	25.78	9.14
σ_{RG}	13.19	15.38	14.09	10.05	13.62	**20.98**	18.76
σ_{YB}	11.04	17.48	11.27	12.23	12.52	15.29	**24.73**
UICM	-0.58	3.11	0.72	2.47	2.22	2.71	**4.33**

Then the underwater image sharpness metric (UISM) and underwater image contrast metric (UIConM) are calculated. The ACE method highest score, 7.06, in UISM measurement, which is closely followed by our method, 7.05. For UIConM measurement, the result of our method stands at the highest level, 0.58, and finally for the comprehensive measurement, underwater image quality metric (UIQM), our method also achieves the highest score. Thus, under this water environment, our method performs best and successfully realizes the color correction and contrast enhancement.

Table 4.6, underwater image quality metric (UIQM) results of diver image (2)

	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*
UICM	-0.58	3.11	0.72	2.47	2.22	2.71	**4.33**
UISM	6.96	**7.06**	6.94	6.84	7.04	6.97	7.05
UIConM	0.34	0.56	0.47	0.51	0.50	0.45	**0.58**
UIQM	0.26	3.52	1.86	3.91	3.24	2.38	**4.28**

Below show the restoration results of another type of image, shoal image. From the integral visual performance, the histogram equalization method fails to restore the degraded image, while other five methods successfully correct and enhance the image to some degree.

(a) (b) (c)

(d) (e) (f)

Figure 4.18, Results on the shoal image. (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

We can derive from Figure 4-18 that only the restoration result of our method is over-enhancement in the top corner of the image, which causes the image seems unnatural. The result of Ancuti et al. is grayish while Galdran et al. is darkish. Meanwhile, the results of ACE method and Fu et al. show greater performance.

Table 4.7, underwater image colorfulness metric (UICM) results of shoal image

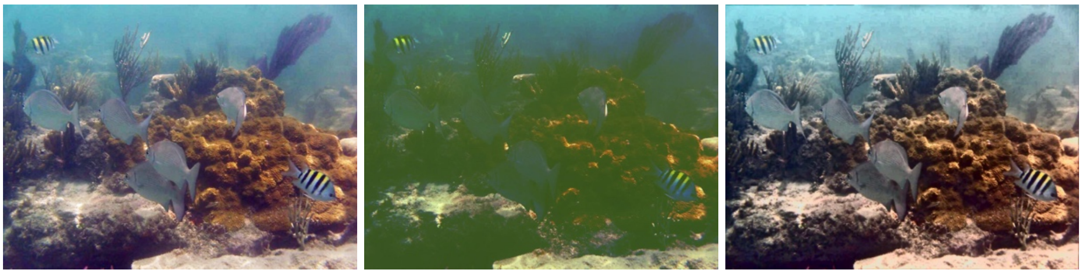
	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*
μ_{RG}	-43.00	-3.89	-42.87	**1.50**	-7.83	-9.64	-12.61
μ_{YB}	28.08	-0.23	32.57	**0.08**	2.46	-7.29	-3.42
σ_{RG}	5.74	12.95	2.24	14.56	6.24	14.17	**22.55**
σ_{YB}	7.87	18.40	1.70	19.50	10.15	19.10	**35.04**
UICM	0.17	3.46	-1.00	3.82	1.67	3.45	**6.26**

Table 4.8, underwater image quality metric (UIQM) results of shoal image

	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*
UICM	0.17	3.46	-1.00	3.82	1.67	3.45	**6.26**
UISM	7.09	**7.17**	5.91	6.81	7.14	7.10	7.05
UIConM	0.21	0.60	0.09	**0.64**	0.38	0.48	0.58
UIQM	1.63	4.16	0.84	**4.34**	3.23	3.53	3.81

In the Table 4.7 and 4.8, we find that although our method achieves greatest performance on colorfulness metric measurements, it fails in the overall evaluation, where the result of Fu. et al gets the highest UIQM score. And ACE method achieves the best performance in UISM.

We finally put the restoration results among these methods of another shoal image as well as their UICM, UISM, UIConM and UIQM values.



(a) (b) (c)

(d) (e) (f)

Figure 4.19, Results on the shoal image (2). (a) ACE. (b) Histogram equalization (HE). (c) Fu et al. (d) Ancuti et al. (e) Galdran et al. (f) Proposed method.

Table 4.9, underwater image colorfulness metric (UICM) results of shoal image (2)

	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*
μ_{RG}	-41.05	-1.46	-27.00	**0.63**	-23.81	-20.30	-15.99
μ_{YB}	30.15	-12.76	29.20	**-2.18**	-13.50	-17.26	-17.98
σ_{RG}	13.81	26.60	5.18	25.36	16.36	19.84	**41.92**
σ_{YB}	12.54	23.70	18.07	22.31	23.03	17.68	**41.22**
UICM	1.59	5.31	1.92	5.30	3.75	3.50	**8.25**

Table 4.10, underwater image quality metric (UIQM) results of shoal image (2)

	Original	*ACE*	*HE*	*Fu.*	*Ancuti.*	*Galdran.*	*Proposed.*
UICM	1.59	5.31	1.92	5.30	3.75	3.50	**8.25**

UISM	6.88	7.05	**7.55**	6.79	6.90	6.88	7.01
UIConM	0.38	0.69	0.39	**0.71**	0.61	0.59	0.69
UIQM	3.44	4.70	3.67	4.69	4.32	4.24	4.77

In general, as discussed above, the proposed method successfully solves the issue of underwater objects visibility enhancement. By comparing with the state-of-art methods, we show that our method performs well on various underwater environments. However, the proposed method also has some drawbacks needed to be solved, for instance, it demonstrates the over-enhancement problem for some test images and some information loss exist as well as the boundary effect. Moreover, by introducing different image evaluation techniques, we deal with a comprehensive analysis and evaluation among the results of different methods, then demonstrates the superiorities and good performance of our method.