A Simulated Water Type Dataset (SWTD) Based on Jerlov Water Types for Underwater Image Quality Analysis

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***Abstract*—The water medium is not particularly conducive for the acquisition of underwater images. This is due to its nature; with the presence of small floating particles in the water medium, causing the scattering of light and attenuation of wavelength, as well as the loss of light, especially in deep water environment. These issues make the captured underwater images less informative, requiring the use of image processing methods to make underwater images more meaningful. To evaluate and compare the performance of different image processing methods, a proper underwater image dataset with various conditions, is of utmost importance. For this purpose, an underwater image dataset; obtained using GOPRO HERO7 SILVER underwater camera, taken at different conditions of underwater environment, has been developed. This manually curated underwater dataset is referred to as Simulated Water Type Dataset (SWTD), and it is based on different water type. The dataset is also made publicly available, which can be used in evaluating image enhancement and restoration methods. A few selected state-of-the-art image processing methods has also been tested on this dataset for illustration purpose, with results analysed quantitatively and qualitatively.**

***Index Terms*—underwater images, image restoration, image enhancement, simulated dataset, Jerlov water types**

I. Introduction

The water surface including oceans, seas and rivers, is massive, covering about 75% of the Earth's surface. It contains a mixture of different compounds and components, including particulate matters, salts, organic compounds, gas bubbles, solvents and a mixture of chemical constituents. Due to the presence of these elements, images captured in the water environment may not reflect the same features and characteristics of the intended object in its entirety; making the environment unfriendly for imaging applications. When light from the object of interest passes through the water to reach the camera, it undergoes absorption, scattering, diffraction and polarization, which reduce image characteristics of the captured underwater image. Image characteristics include hue, saturation, chroma, brightness, sharpness and contrast. Consequently, the acquired image becomes less informative and of less use for different applications. Hence, image processing algorithms are required to enhance the acquired images and improve their characteristics. Image restoration and enhancement methods are most widely used in this field, in order to make underwater images more applicable to applications including target detection, classification of marine organisms [1], remotely operated vehicles, navigation and Autonomous Underwater Vehicles (AUVs) [2], [3], seabed scene 3D reconstruction [4], and underwater robotics.

Image enhancing techniques commonly concentrate on improving visibility properties of an image such as brightness, contrast, sharpness, saturation, hue and chroma. However, other than visibility properties, degraded signal properties are commonly not dealt by enhancing techniques. Hence, restoration process is required, which relies on underwater Image Formation Model (IMF) to restore the degraded signal properties by deriving each term in the IMF.

To ensure the effectiveness of a particular image processing method, resultant processed images need to be properly evaluated once the acquired images have been processed. Some non-reference quality metrics have been developed for evaluating underwater images, including Underwater Colour Image Quality Evaluation (UCIQE) [5] and Underwater Image Quality Evaluation (UIQM) [6], which focus on evaluating the values of hue, saturation, variance and chroma of the processed underwater image. However, evaluation of underwater images using these non-reference tools do not properly analyse the signal properties of the resultant images, with only colour properties given importance. Alternatively, full reference quality metrics, including Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Mean Square Error (MSE) [7], may be used to evaluate the effectiveness of the methods; based on the noise and structural properties of the resultant images. These full reference evaluation tools would commonly require an undistorted reference image or a ground truth image. Whilst this is possible for aerial images; where ground truth image can be obtained with relative ease, capturing undistorted reference image or ground truth of an underwater image in its challenging environment may not be possible. As such, there is a need for an efficient dataset

Manuscript received February 22, 2021; revised August 25, 2021.

doi: 10.12720/jait.12.4.334-341

along with proper reference images, for the purpose of evaluation of enhancement and restoration methods.

As such, a method of creating a Simulated Water Type Dataset (SWTD) for underwater images dataset from ground truth images, is given in this paper. The SWTD dataset is simulated based on the Jerlov water types [8], and has been made publicly available, to facilitate other researchers in evaluating different image processing methods.

II. Literature Survey: Underwater Enhancement, Restoration and Dataset

Generally, image enhancement methods work on improving visibility characteristics of the image; including contrast, histogram, colour constancy, brightness and sharpness, rather than its structural properties. Hummel [9] and Zuiderveld [10] propose traditional enhancement methods, based on histogram transformation of colour channels and histogram equalization, respectively. These methods focus more on increasing contrast of an image, however, it may also increase noise of an image as well. Ancuti *et al.* [11] propose a fusion strategy to enhance images, by considering several filters. On the other hand, Iqbal *et al.* [12] propose a method for enhancement by adjusting colour contrast of an underwater image, before equalizing its saturation. Subsequently, they improved this algorithm by using enhanced unsupervised colour correction model [13]. Huang *et al.* [14] focus on shallow underwater image, by proposing enhancement method using histogram stretching approach.

Due to limitations on enhancement methods, researchers have also proposed different restoration methods to process underwater images, particularly to deal with degraded signal properties of the captured underwater image. Reference [15] provides a detail review of underwater image restoration methods. Carlevaris-Bianco *et al.* [16] propose a method for restoring underwater images by estimating depth, based on strong attenuation prior difference between the three channels, considering the channel with maximum intensity prior. He *et al.* [17] introduce Dark Channel Prior (DCP) for the recovery of hazy images, and subsequently, it has also been applied for the restoration of underwater image. The method relies on the assumption that dark pixels in an image are those that are close to the camera, whilst bright pixels are those that are far-away from the camera. Liu *et al.* [18] has also applied DCP for the removal of scattering effects from water in an underwater image. Similarly, Drews *et al.* [19] have considered restoration by using DCP, but by utilizing the green and blue channels only. Similarly, Li *et al.* [20] propose a blue-green channel restoration method by extending DCP and dehazing red channel using Gray-World assumption theory. In reference [21], DCP has also been used to restore underwater images, by refining depth map using median filter instead of the general soft matting filter. Wen *et al.* [22] improve the restoration process by considering attenuation coefficients, rather than just utilising the darkest channel. A depth estimation method to develop transmission map, and subsequently, for the restoration of scene radiance has been proposed by Peng *et al.* [23]. Song *et al.* [24] propose an alternative depth map estimation strategy, involving the formation of depth map based on the attenuation priors of each channel, to allow the extraction of background light and transmission map from estimated depth map.

For all these enhancement and restoration methods, reference images are needed to appraise the effectiveness of the methods, and to allow comparison with other available methods in the literature. As reference underwater images are relatively challenging to obtain, a few researchers have provided simulated seawater environment as underwater image dataset to allow performance measures between different enhancement and restoration methods. Lu [25] has selected 30 underwater images, including 15 images from the internet and 15 images from his water tank experiments, by simulating seawater with different turbidity by increasing the amount of sea soil to the seawater. However, the method considers only soil addition for increasing turbidity, whereas other major factors of seawater have been neglected.

Duarte *et al.* [26] propose the 3D TURBID database for evaluating underwater image restoration. The database provides more information about the characteristics and structures with real seabed images, obtained from the Bahamas. Three different high-quality photos were placed at the bottom of a water tank, with two LED lamps in a box made of reflector and diffuser materials strategically placed to ensure continuous and uniform lighting. Turbidity of the water was varied by adding whole milk into the water, to produce 19 different levels of turbidity, with 30 images taken for each level of turbidity. However, a study [27] has highlighted that milk, with its larger sized particles induces a lot of wide-angle scattering, and subsequently, increases backscattering effect; making the captured images dissimilar from real underwater images. Jian *et al.* [28] propose a database for underwater salient object detection called OUC-VISION underwater image database. It contains a total of 4,400 images with 220 individual objects, with ground truth information. A cube pool camera and a lighting system with six LED lights have been designed to simulate a realistic underwater environment, and water turbidity is increased by adding soil to the water, to generate three levels of turbidity. However, the OUC-VISION underwater image database suffers from a number of disadvantages such as improper lighting conditions, simulated turbidity water instead of real lake or sea water, and limited number of water types only considered.

It is obvious from the above that underwater images database is required, for researchers to compare the performance of different enhancement and restoration methods. Ideally, the collections of underwater images need to be sufficiently large, to allow meaningful analysis and performance measure. Additionally, real high turbidity sea water needs to be used to mimic as close as possible real underwater conditions, whilst considering the different water types.

III. Simulated Water Type Dataset

The Simulated Water Type Dataset (SWTD) is a collection of simulated underwater images; with the images created using a 4 feet pool, with 250 litres of water.

Given the radiance $J^c(x)$ of an object of interest in an underwater environment, the acquired image $I^c(x)$ at the camera, is commonly described according to the Image Formation Model as shown in equation 1, as the radiance $J^c(x)$ of the object travels towards the underwater camera.

$$I^c(x) = J^c(x).t^c(x) + \left(1 - t^c(x)\right).B^c \qquad (1)$$
$$c \in \{R, G, B\}$$

In the above equation, $J^c(x).t^c(x)$ describes the radiance $J^c(x)$ of the object as it travels in the underwater medium, whilst $\left(1-(x)\right).B^c$ represents the scattering of background light B^c as it travels towards the camera. Transmission map $t^c(x)$ describes the part of the object radiance without distortion that reaches the camera. This is dependent on the object's distance from the camera $\tilde{d}(x)$ or its depth, and the water attenuation coefficient β_c in colour channel $c \in \{R, G, B\}$:

$$t^c(x) = e^{-\beta^c \tilde{d}(x)}, \quad c \in \{R, G, B\} \qquad (2)$$

From equations (1) and (2), it can be seen that radiance $J^c(x)$ of the object is attenuated exponentially with depth and attenuation coefficient. Whilst depth $\tilde{d}(x)$ represents the object's distance from the camera, the water attenuation coefficients are dependent on water types as well as the colour channel.

Jerlov [8] studies the properties and characteristics of sea water, and has broadly classified it into two classes, namely; oceanic and coastal waters. These broad classifications are again sub-divided into type-I, type-IA, type-IB, type-II and type-III for the oceanic water, and type-1C, type-3C, type-5C, type-7C and type-9C, for the coastal water; with the first and last sub-categories for each water class representing the clearest and most turbid water, respectively. As transmission map; which is partly dependent on attenuation coefficient, has a vital role in underwater computer vision, different attenuation coefficient values have been derived [8], for different wavelength of red, green and blue channels, shown in Fig. 1, which is taken from [29]. The wavelength considered ranges from 310 nm to 700 nm, which is the range of red, blue and green lights underwater. Shades of each type, ranging from clear to turbid is shown in Fig. 2, which is acquired from [30].

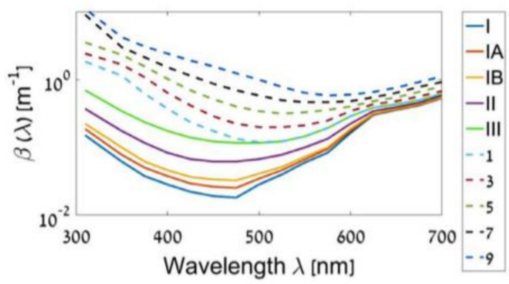


Figure 1. Ten water types and their respective attenuation coefficients [29].

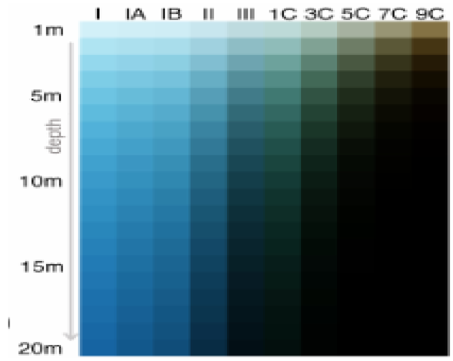


Figure 2. Visual shades of the ten water types [30].

In order to capture the effect of underwater image formation, the Simulated Water Type Dataset (SWTD) are carefully curated based on different Jerlov water types [8]. The captured images are taken in a controlled environment, using three types of Light Emitting Diodes (LED) lighting: high-illuminator (H-type), medium-illuminator (M-type) and low-illuminator (L-type), for creating the required lighting environment and to avoid external lighting. A GOPRO HERO 7 SILVER underwater camera was used to capture the images. Captured images are instantly transferred to the working system. Actual sea water has been used to generate the images. Images for this dataset are generated based on different water types, by employing two shades of turbidity developer inks: blue (B-Type) and brown (BR-Type) turbidity developer. This dataset can be found at https://github.com/JarinaRaihan/SIMULATED-DATASET.

The object of interest is kept underwater with clear, undistorted water whilst generating the ground truth reference image. For each water type, the turbidity developer inks are used, and their concentration is varied accordingly. As seen in Fig. 2, types I, IA, IB, II, III, and 1C are created using different shades of blue developer, whilst types 3C, 5C, 7C, and 9C are created using shades of brown developer. Different shades of water; by using different lighting as well as type and concentration of developer inks, are considered. Table I provides combinations of lighting conditions and developer type used to generate the different water types.

TABLE I. Conditions for Creating Dataset Based on Jerlov Water Types [8]

Water types	Lighting condition type	Developer type
Type I	M-Type	10ml-B-Type
Type IA	M-Type	20ml-B-Type
Type IB	H-Type	20ml-B-Type
Type II	H-Type	10ml-B-Type
Type III	M-Type	20ml-B-Type
Type 1C	M-Type	30ml-B-Type
Type 3C	H-Type	30ml-B-Type
Type 5C	L-Type	40ml-B-Type
Type 7C	L-Type	10ml-BR-Type
Type 9C	L-Type	30ml-BR-Type

A few selected state-of-the-art enhancement and restoration methods, have been chosen to test the created

SWTD; with output from the different methods analysed qualitatively and quantitatively. Qualitative analysis employs visual evaluation of processed underwater images, whilst quantitative analysis utilizes reference and non-reference performance measures.

Quantitative evaluation is an important tool in proving effectiveness of any enhancement or restoration methods; as it can be more easily used to compare between different methods. Both full reference evaluation (PSNR and SSIM [7]) and non-reference evaluation (UCIQE [5] and UIQM [6]) are used to evaluate performance of the different enhancement and restoration methods. UCIQE and UIQM are evaluated as follows:

$$\text{UIQM} = C_1 * \sigma_c + C_2\, con_l + C_3 * \mu_s \qquad (3)$$

$$\text{UIQM} = C_A * \text{UICM} + C_B\, \text{UISM} + C_C * \text{UIConM} \qquad (4)$$

where $C_1 = 0.4680$, $C_2 = 0.2745$, $C_3 = 0.2576$, and σ_c, con_l and μ_s are the standard deviation of chroma, contrast of luminance and average of saturation of the image, calculated as in reference [5]. $C_A = 0.0282$, $C_B = 0.2953$, $C_C = 3.5753$, and Underwater Image Colourfulness Measure (UICM) , Underwater Image Sharpness Measure (UISM), Underwater Image Contrast Measure (UIConM) , are colourfulness, saturation and contrast measures of the image, calculated, as defined in reference [6].

IV. Results

Fig. 3 and Fig. 4 show the simulated dataset for oceanic and coastal water types, respectively. The synthesized type 9C underwater image from coastal water category given in Fig. 4(f), represents the most turbid in this category, and is almost invisible due to low lighting conditions and high concentration of brown developer. Similarly, oceanic water category type IB is chosen from Fig. 3. One type from oceanic and coastal water types each is used. These original synthesis images are used as input for the enhancement methods in coastal and oceanic waters types, and are shown in Fig. 4(f) and Fig. 3(d), respectively.

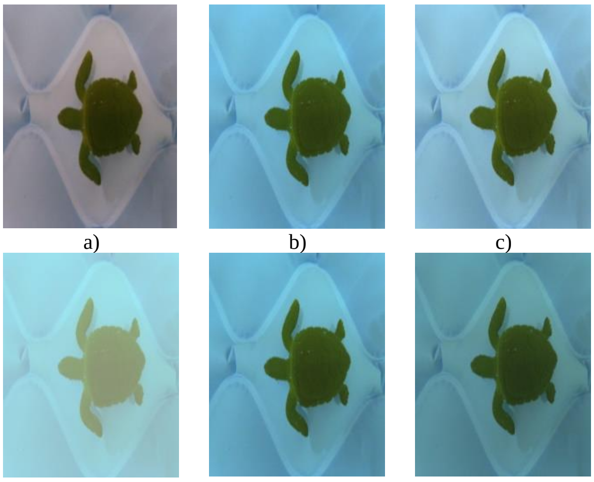


Figure 3. Image showing ground truth and simulated oceanic water types a) ground truth image, b) Type I, c) Type IA, d) Type IB, c) Type II, d) Type III.

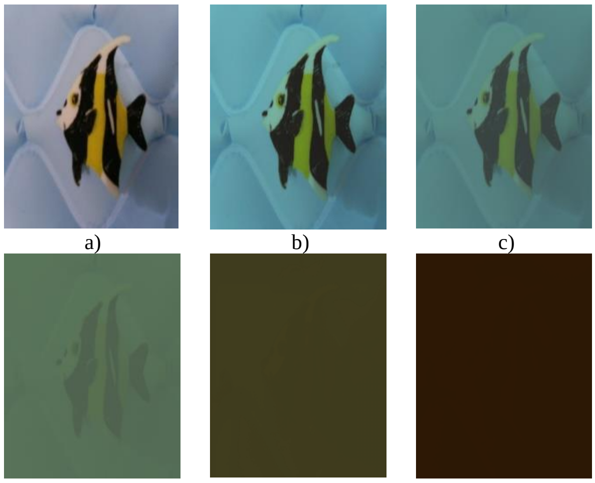


Figure 4. Image showing ground truth and simulated coastal water types a) ground truth image, b) Type 1, c) Type 3C, d) Type 5C, e) Type 7C, f) Type 9C.

A. *Qualitative Evaluation of Underwater Image Processing Methods Using Synthesis Images*

1) Qualitative analysis of output from enhancement methods

Fig. 5 shows outputs from enhancement methods on a simulated coastal underwater image in Fig. 4(f). As can be seen from the figure, all enhancement methods do not provide exact recovery as the ground truth reference image, in Fig. 4(a).

Generally, the enhancement methods manage to improve brightness and contrast. Ancuti *et al.* [11] and Iqbal *et al.* [12] provide good enhanced results, with both methods utilising a colour correction algorithm. On the other hand, Hummel [9], which is based on histogram transformation method, produces over saturated image. Huang *et al.* [14] focus on enhancement for shallow water images which is similar to coastal environment, to produce a satisfactory albeit over-brightly processed image. It is highlighted that Iqbal *et al.* [13] and Zuiderveld [10] are unable to enhance the turbid image very well.

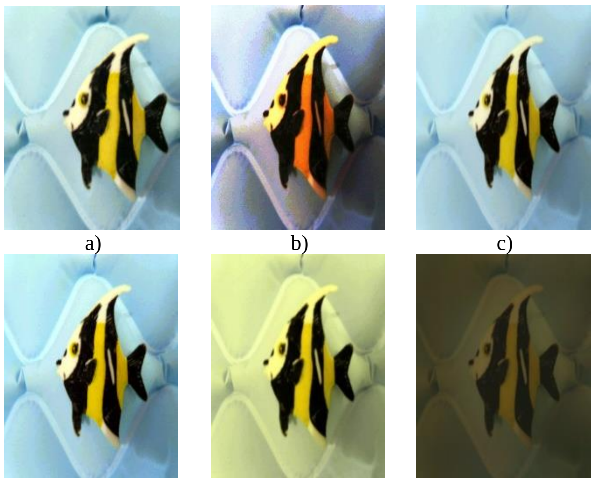


Figure 5. Qualitative analysis of enhancement methods namely: a) Ancuti *et al.* [11], b) Hummel [9] c) Iqbal *et al.* [12] d) Huang *et al.* [14], e) Iqbal *et al.* [13] and f) Zuiderveld [10].

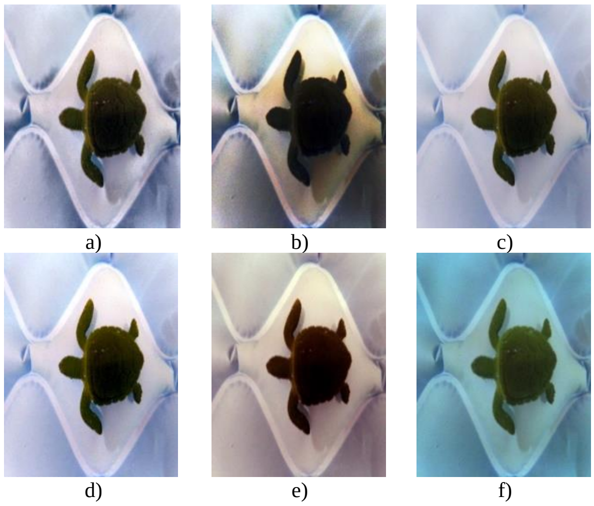


Figure 6. Qualitative analysis of enhancement methods namely: a) Ancuti *et al.* [11], b) Hummel [9] c) Iqbal *et al.* [12] d) Huang *et al.* [14], e) Iqbal *et al.* [13] and f) Zuiderveld [10].

For images taken in milder turbid conditions such as the oceanic category image shown in Fig. 3, where the background colour does not get affected, Fig. 6 depicts processed images using different enhancement methods. Generally, enhancement methods do not focus on improving degraded signal properties of the image, but rather only the colour quality properties of the image. As can be seen from Fig. 6, none of the considered enhancement methods manage to enhance the image close to the ground truth reference image in Fig. 3(a). Ancuti *et al.* [11], Hummel [9] and Iqbal *et al.* [12] give over saturated results, whilst Huang *et al.* [14] and Iqbal *et al.* [13] give over exposed results. On the other hand, Zuiderveld [10] provides an over contrast image.

It can be seen from the analysis that enhancement methods can improve colour quality of the images very well, and hence, they are more suitable for images taken in heavy turbid conditions. However, for low turbid images, enhancement methods provide unwanted contrast, saturation and over brighten output images, making them less informative.

2) Qualitative analysis of restoration methods

The synthesized dataset, particularly, water type 9C from the coastal water category in Fig. 4(f), and water type 1B in Fig. 3(d), are fed to selected state-of-the-art restoration methods for visual evaluations. Results obtained from processing water type 9C are given in Fig. 7. It can be seen from the results that none of the restoration methods perform well in the most turbid coastal water images; due to its muddy conditions and distortions. Yang *et al.* [21] produce a relatively good processed image among the methods considered, with its result closer to the ground truth reference image given in Fig. 4(f). The method proposed by Yang *et al.* [21] is based on dark channel prior, and as its name suggests, the darkest channel is commonly chosen as red, which normally happens in a dark image. Peng *et al.* [23] also perform well, after Yang *et al.* [21], with the method estimating depth as an intermediary step to provide a better restoration result. He *et al.* [17], Carlevaris-Bianco [16] and Liu *et al.* [18] produce almost similar results. Li *et al.* [20], Song *et al.* [24] and Wen *et al.* [22] do not perform well with the most turbid image. However, generally, results from the enhancement methods (Fig. 5) perform way better than the restoration methods (Fig. 7). This is because enhancement methods generally work on improving colour quality of an image; advantageous for coastal water images which are generally dull and darker. On the other hand, restoration methods restore degraded signal properties, but fail in colour correction process. So, these restoration methods must be designed to choose proper prior, and as such, they may be utilised in different turbidity conditions.

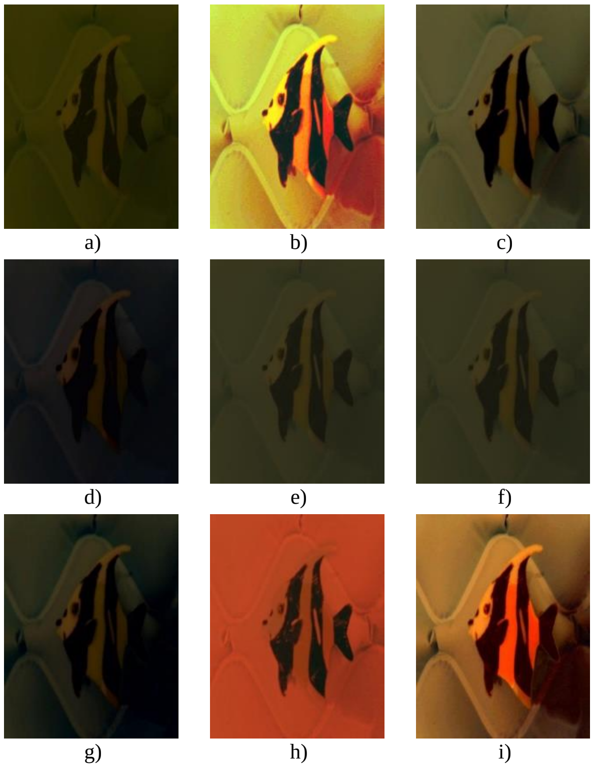
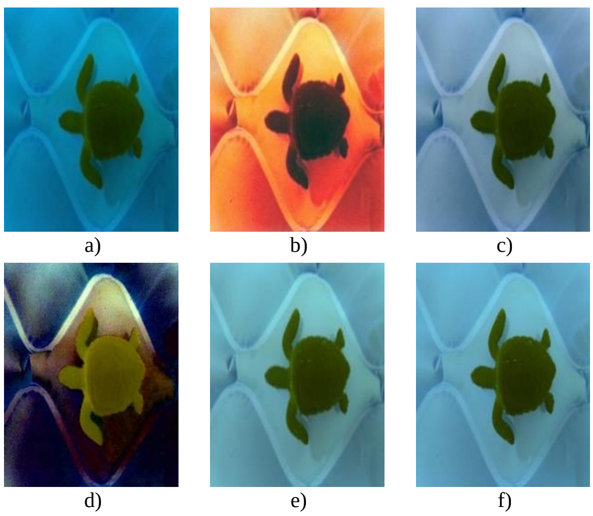


Figure 7. Qualitative analysis of restoration methods namely: a) He *et al.* [17], b) Li *et al.* [20], c) Peng *et al.* [23], d) Yang *et al.* [21], e) Carlevaris-Bianco [16], f) Liu *et al.* [18], g) Drews *et al.* [19], h) Song *et al.* [24], i) Wen *et al.* [22].



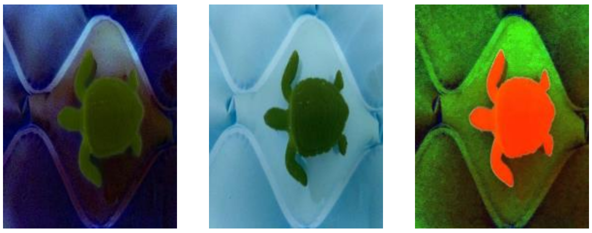


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Figure 8. Qualitative analysis of restoration methods, namely: a) He *et al.* [17], b) Li *et al.* [20], c) Peng *et al.* [23], d) Yang *et al.* [21], e) Carlevaris-Bianco [16], f) Liu *et al.* [18], g) Drews *et al.* [19], h) Song *et al.* [24], i) Wen *et al.* [22].

Fig. 8 depicts processed image using selected restoration methods with mild turbidity oceanic water category type IB shown in Fig. 3(d). Peng *et al.* [23] give the best output image, which is almost similar to the original image. Carlevaris-Bianco [16], Liu *et al.* [18] and Song *et al.* [24] perform well, producing good output images, albeit with slightly higher contrast than the ground truth reference image.

On the other hand, Yang *et al.* [21] and Drews *et al.* [19] cannot restore the underwater images well, producing highly saturated output images. Similarly, Li *et al.* [20] and Wen *et al.* [22] give poor performance.

From the analysis above, designs of restoration methods need to be improved such that the methods work on all underwater conditions and different levels of turbidity, instead of concentrating only on few milder conditions. Current restoration methods which produce excellent results for underwater image under coastal water category, are not able to restore very well in oceanic category and vice versa.

B. *Quantitative Evaluation of Underwater Image Processing Methods Using Simulated Images*

Both full reference evaluation (PSNR and SSIM [7]) and non-reference evaluation (UCIQE [5] and UIQM [6]) are used as performance metrics; to quantitatively appraise the selected state-of-the-art enhancement and restoration methods.

1) Quantitative analysis of the enhancement methods

Table II shows the PSNR, SSIM, UCIQE, and UIQM values for the enhancement methods using on the generated SWTD. To evaluate the algorithms quantitatively, most commonly used quality metrics are Peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM), UCIQE, and UIQM, as shown in Table II. The higher these values, the better the algorithm. The enhancement methods work on improving the colour quality and properties of the image, with the SWTD having a combination of images at low turbid as well as high turbid conditions.

Ancuti *et al.* [11] propose a fusion strategy which outperforms other methods in non-reference metric category. Iqbal *et al.* [13] and Huang *et al.* [14] provide good results in full-reference category. However, traditional methods, such as methods proposed by Zuiderveld [10] and Hummel [9] which work on the histogram of the image, provide average results. Thus, enhancement algorithms may work efficiently on designing algorithms based on hybrid strategies, which are a combination of a few traditional approaches to enhance the image.

TABLE II. QUANTITATIVE EVALUATION OF UNDERWATER ENHANCEMENT ALGORITHMS

Method	**PSNR ↑**	**SSIM ↑**	**UCIQE ↑**	**UIQM ↑**
Zuiderveld [10]	9.05	0.33	0.55	1.42
Hummel [9]	4.66	0.19	0.63	1.34
Iqbal *et al.* [12]	9.80	0.42	0.66	1.71
Iqbal *et al.* [13]	**11.58**	0.46	0.52	1.41
Huang *et al.* [14]	8.12	**0.48**	0.69	1.75
Ancuti *et al.* [11]	10.23	0.25	**0.75**	**1.84**

2) Quantitative analysis of restoration methods

Table III shows average results of the restoration methods on the SWTD. To analyse the methods quantitatively, most commonly used quality metrics are PSNR, SSIM, UCIQE, and UIQM. Method by Peng *et al.* [23] utilises depth estimation to restore the images well, to give a good PSNR and UCIQE. The method gives good metric values for both reference categories. Yang *et al.* [21] and Carlevaris-Bianco [16] also perform well, with better scores in SSIM and UIQM, respectively. The traditional methods; He *et al.* [17], Drews *et al.* [19] and Liu *et al.* [18], give average results since the methods are not suitable for high turbidity conditions.

TABLE III. QUANTITATIVE EVALUATION OF UNDERWATER RESTORATION METHODS

Method	**PSNR (↑)**	**SSIM (↑)**	**UCIQE (↑)**	**UIQM (↑)**
He *et al.* [17]	8.45	0.35	0.65	1.61
Li *et al.* [20]	2.97	0.24	0.24	1.18
Peng *et al.* [23]	**16.70**	0.55	**0.91**	1.45
Yang *et al.* [21]	11.02	**0.62**	0.15	1.02
Carlevaris-Bianco [16]	7.23	0.31	0.55	**1.72**
Liu *et al.* [18]	10.09	0.27	0.54	1.43
Drews *et al.* [19]	5.54	0.62	0.70	1.27
Song *et al.* [24]	9.76	0.41	0.58	1.51
Wen *et al.* [22]	1.21	0.32	0.19	1.49

V. CONCLUSION

Underwater image dataset with related ground truth reference images, are needed to compare the performance between different underwater enhancement and restoration methods. In this paper, a Simulated Water Type Dataset (SWTD) have been developed, based on Jerlov water types; to provide underwater images with a variety of underwater imaging conditions and environment. Since, the dataset has proper reference images, it is very well suited for evaluation of different enhancement and restoration methods via full reference image quality metric tools. The SWTD is created in a controlled environment using real sea water. Several image processing methods have been analysed, quantitatively and qualitatively, to determine the effectiveness of the different methods. From the analysis, it can be concluded that enhancement algorithms work well in high turbid conditions, however, lack performance in low turbid images. This may be due the designs of enhancement methods, which generally focus on improving visibility conditions of the image but not the signal and structural properties. Generally, restoration method gives good performance in low turbid images, since images retain their colour properties in low turbidity. Performance is, however, poor for high turbid images due to the loss of original colour in those images. Thus, in the selection of suitable image processing algorithms, it needs to combine both enhancement and restoration approaches; in order to take advantages of both approaches, to satisfy all the different imaging conditions in underwater environment.

Finally, the dataset created can be used to evaluate the performance of any underwater image processing methods; to appraise their applicability in different underwater applications. At present, 33 underwater images are available in the dataset; with 3 ground truth and 30 simulated underwater images for different water types. In the future, the dataset can be extended by adding more ground truth and simulated images, so that it can be more extensive. Furthermore, the work can be extended by varying distance between the object of interest and the camera; such that depth of the acquired images may be varied. The volume of images obtained may then be used for evaluating different image processing methods that involve machine learning and deep learning techniques for algorithm development; by encompassing different underwater environments as well as circumstances.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Jarina Raihan A conducted the research work, experiments and created the manuscript. Pg Emeroylariffion Abas and Liyanage C De Silva reviewed the paper and helped in improving the experiments conducted. All authors had approved the final version.

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