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UIETM: Underwater Image Enhancement Based on Modified Transmission Map

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Abstract : Underwater sensors are used to explore undersea resources, seafloor mapping, archaeology, underwater monitoring and tracking. As a result, the underwater sensors are critical because it helps to obtain high quality information from the underwater world. In underwater environment, light attenuation and backscattering leads to color degradation, limited contrast, blurred images and low brightness. So, the underwater image formation model highly relies on background light and transmission light. In this work, a Underwater Image Enhancement Based on Modified Transmission Map (UIETM) algorithm is proposed based on the image formation model. The proposed UIETM, includes backscattering and transmission estimation network that improves the overall quality of degraded underwater images. The performance of UIETM is compared based on the quantitative and qualitative analysis. The quantitative analysis is conducted based on niqe, uiqm and brisque evaluation metric. The experimental results shows that the proposed UIETM network outperforms the existing underwater image enhancement algorithms based on traditional and deep neural network algorithms.

Keywords: Color Correction; Transmission Map; Underwater images; Underwater image formation model; Underwater image enhancement.

Introduction

During the last few years, the importance of image processing for underwater robots has received a lot of attention. Under-water robots (such as automated under-water vehicle and remotely operated vehicle) mainly depend on vision sensors to gather data about the under-water environment and marine life. Underwater robots face challenges in obtaining data due to its physical properties such as non-uniform lightning, color cast, and limited range of visibility [1]. Due to the complex under-water properties the existing under-water image enhancement (UIE) methods does not perform well [3], [4]. As the captured under-water images usually appear blue, green, and blue-green with an increase in depth.

Moreover, the captured under-water image usually suffers from faded color, limited visibility, uneven lightning and poor contrast. Due to under-water medium change from air to water the light intensity decreases. The decrease in intensity depends on the color wavelength [3]. The reduction of light intensity is known as light attenuation. The light attenuation occurs because of scattering and absorption phenomenon. The level of under-water visibility decreases around 20m in clean water and less than 5m in turbid water [4]. The light travelling through the water loses its intensity depending on the wavelength of color. The longest wavelengths, with the lowest frequency, are absorbed first i.e., red color. The red color starts losing the intensity just after 1m and disappears at about 4 5m distance [5] as shown in Fig. 1a. Therefore, images captured under-water seems to be blue (shortest wavelength).

The images obtained under-water suffer from distorted color and contrast. Hence, the crucial information of the under-water image is lost. As a result, under-water image processing approaches are required to enhance the image contrast and color to extract the lost information. To improve the contrast of the degraded image usually contrast based enhancement methods are applied on the image [6]. The existing UIE methods focus on contrast enhancement [5] but, does not consider the important parameters of the under-water image. In order to resolve issues, a

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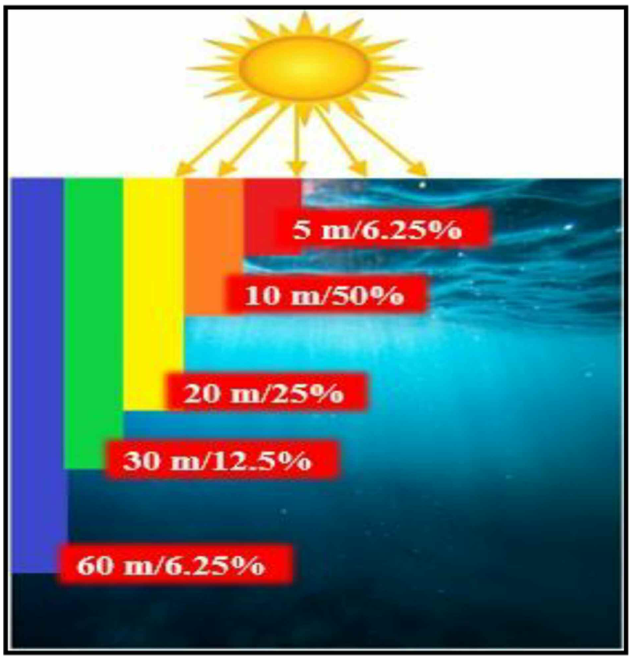
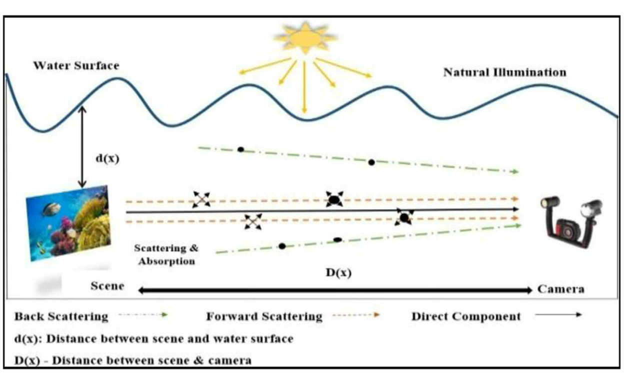
modified transmission light estimation method is proposed. In the past few years, deep neural based techniques have advanced rapidly, and they are now widely used in image processing tasks [7-9]. The deep neural based approaches show enhanced performance in the object tracking, detection [10], recognition tasks [12]. Deep learning approaches shows improved performance in terms of low vision and high vision task [12]. Moreover, image super resolution [13], image de-blurring and image de-noising tasks are also performed using deep learning-based approaches. Despite the fact that deep learning-based approaches give appealing results but depend on several parameters (epoch, training size and hyper-parameters). However, the deep neural based techniques highly rely on the large number of datasets. But due to the complex under-water environment it is difficult to obtain the degraded image and ground truth respectively.



(a)



(b)

Fig 1. (a) The visual illustration of the diminishing of color in under-water environment. (b) The pictorial representation of under-water image formation model.

The major highlights of the paper are mentioned below:

(i) The UIETM, is used to compute the modified transmission map based on double exponential function to compute attenuation coefficient, that estimates the direct light that reaches the camera without scattering.

(ii) The UIETM, is used to compute the attenuated light using the proposed attenuation coefficient.

(iii) The UIETM, uses the wavelength information of red, blue and green color to estimate the attenuation coefficient that helps in regaining the attenuated color.

The paper consists of 5 sections. Section 1, discusses need of UIE process and challenges behind it. Section 2, discusses the background study of UIQM and existing methods to estimate the transmission map. Section 3, presents the proposed U-TMBL method. Section 4, analyses results based on qualitatively and quantitative results. Section 5, gives the conclusion of the paper.

Background Study

The existing literature survey is discussed based on the under-water image formation model (UIFM).

The UIFM

The underwater image formation model (UIFM) is same as Jaffe McGlamery [14]. The UIFM is the most used image formation model which is also similar to hazy image formation model as shown in Fig. 1b. Eq. 1, shows the mathematical representation of UIFM:

$$I_C(x,y) = J_C(x,y)\,t_C(x,y) + B_C(1 - t_C(x,y)) \quad \ldots(1)$$

where Bc is the background light, Jc (x, y) is the clear image, Ic (x, y) is the degraded under-water image at (x, y), c belongs to the color channel and tc (x, y) is the estimated transmission light map. It is the remaining light that is obtained at the camera after the scattering and absorption of the light. The tc (x, y) is computed using Eq.2

$$t_c\,(x,y) = e^{\beta_c d(x)} \quad \ldots(2)$$

where βc is the total attenuation coefficient at color channel c that is considered as constant value for each c and d(x) is the estimated scene depth. That implies that tc (x, y) can be obtain, if the scene depth d(x) is known.

Note, Eq.2 is considered when haze is homogeneous. The Jc(x, y) can be enhanced by removing haze from Ic(x, y). The Jc(x, y) is the portion of incident light that is reflected through reflectivity. Moreover, the incident light includes artificial light and the environmental illumination. Therefore, the degraded color and veiling light may occur in Jc(x, y), due to the impact of the artificial light source and natural illumination along the path.

Transmission Map Estimation

To computer the transmission maps several methods have been proposed among which the dark channel prior (DCP) [15] is most used. The DCP assumes that at least one pixel of three RGB channels will have low intensity value in non-sky patch. Also, due to strong attenuation of the red channel, the DCP considers only green-blue channel. This is described in Eq. 3.

$$J_{dark}^{rgb}(x) = \min_{y\in\mathbf{\Omega}}\left\{\min_{c} J^{c}(y)\right\} = 0 \quad \ldots(3)$$

After that minimum filter is applied on Eq. 3 and then divided by background light Bc. The resultant is given by Eq. 4.

$$\min_{y\in\mathbf{\Omega}}\{\min_{c}\frac{I^{c}(y)}{B^{c}}\} = \min_{y\in\mathbf{\Omega}}\left\{\min_{c} J^{c}(y)\right\} + 1 - t_{DCP}(x) \quad \ldots(4)$$

The transmission map is estimated using Eq. 5

$$t_{DCP}(x) = 1 - \min_{y\in\mathbf{\Omega}}\{\min_{c}\frac{I^{c}(y)}{B^{c}}\} \quad \ldots(5)$$

Furthermore, Drews [16] introduced tDCP

(x) in which Ic(y) is replaced by Ic' (y). To estimate the transmission map, the maximum intensity prior method is used as shown in Eq. 6

$$\begin{cases} D_{mip}(x) = max\, y \in \Omega - I^{r}(y) - y \in \Omega\max(I^{c'}(y)) \\ t_{MIP}(x) = D_{mip}(x) + 1 - \max(D_{mip}(x)) \end{cases}$$

...(6)

To estimate the scene depth of the under-water image, the stretching is performed on 3 depth maps consisting of the maximum intensity dD, the image blurriness dB and the red channel dR maximum filter as shown in Eq. 7

$dn = \theta b[\theta a dD + (1-\theta a)dR] + (1-\theta b)dB$

...(7)

where θb and θa are based on same sigmoid function. Then, the depth map is further enhanced using the guided filter. At last, the relative distance is transformed as per the actual distance to obtain the final depth df of the image. Eq. 8 presents the transmission map estimation of the attenuated red channel.

$tr(x) = e - \beta r d f$ .... (8)

where $\beta r \in \left(\frac{1}{8}, \frac{1}{5}\right)$ as per [17,18]. Furthermore, the transmission map of the green and blue channels is calculated using their attenuation ratios with respect to the red channel [19].

The proposed UIETM

In comparison to conventional UIE approaches, a novel UIETM method is pro- posed to enhance the under-water images. The UIETM method includes three steps: (i) Scene depth estimation (d(x))- uses inverse red-channel attenuation in- verse red-channel attenuation [20] (ii) Background light estimation Bc, improves the color and contrast of the image [21](iii) Modified Transmission estimation tc, uses novel attenuation coefficient that uses scene depth and further refined by guided filter and box filter. Finally, the enhanced image is obtained using the mentioned steps.

The UIETM also uses the wavelength information to estimate the attenuated color. However, the existing methods did not consider the wavelength information. Moreover, UIETM uses camera response function as it plays a major role in image enhancement process.

(i) Scene depth estimation (d(x))- The traditional DCP does not perform well on complex under-water images due to under-water small particles (such as phytoplankton) and uneven lightning which impacts the transmission map of the image. The normal light attenuations of red are 18%, green is 5%, and blue channel is 2.5% travelling under the water. After considering the strong relation of the scene depth (the distance between the object and the camera) with the wavelength, the scene is estimated considering the limited lightning case.

Whenever the under-water image is captured in low-light conditions, following condition is observed where the ratio of the mean intensity of the red channel and the maximum intensity between blue and green channel should be small. The ratio is presented in Eq 9.

$$R = \frac{mean(I^{red})}{\max(mean(I^{green}), mean(I^{blue}))} \quad \ldots(9)$$

This shows the foreground area is bright whereas the background area is dark of the image. In these instances, inverse red channel attenuation, which is described in [20], reflect the unique properties of an under-water image. The scene points that obtain small values in Eq. 10 are presumed to be near to the camera.

$$A^{invred}(x) = \min_{x' \in \Omega(x)} (1 - I^{red}(x')) \quad \ldots(10)$$

The Eq. 11 is used to estimate the final scene that is obtained with the computation of the original distance between the object and the camera.

$d'(x)$=($d(x)$+ε) ...(11)

where, ε, is the closet point near the camera. The ε is the distance between the closest estimated scene point and camera and $d(x)$ is the scene depth.

(ii) BL Estimation (Bc)- The Bc estimati9on is the main factor that can improve the color and contrast of the image. However, the smaller value of Bc leads to more degraded image whereas the higher value of the Bc leads to better visual results. The background light is estimated using [21].

(iii) Transmission map(tc)- The UIFM requires the estimation of the background light and transmission light. Usually, the tc is estimated with [22-23]. But, due to color degradation the DCP sometimes do not perform well on complex under-water environment. In UIETM, a modified transmission map is proposed that is further refined using the guided filter. The tc is transparent layer that includes the depth information. The proposed is shown in Eq. 12 where transmission is estimated using weights of single exponential method and the color information of all three channels based on wavelengths.

$$t^c = me^{-\left(\int_{400}^{600} \beta^c s(\lambda)\, d\lambda\right) D'(x)} + ne^{-\left(\int_{600}^{750} \beta^c s(\lambda)\, d\lambda\right) D'(x)} \quad \ldots(12)$$

where m and n are weights of the exponential function. The value of m = 0.6 and n = 0.4. The βc is the adaptive attenuation coefficient depending on each wavelength and the s(λ) is the spectral sensitivity of each wavelength based on the camera response function of CMV12000 camera [24]. Finally, the tc is estimated 12. If tc obtains zero that means the image contains unwanted noise. So, we considered a bound t0. The proposed method shows superior performance with the modified transmission map estimation and background light estimation. Finally, clear under-water image is obtained using the Eq. 13.

$$J^c(x) = \frac{I^c(x) - B^c}{\max(t_c(x), t_0)} + B^C \quad \ldots(13)$$

Evaluation and Analysis

The effectiveness of the proposed UIETM is analysed using the real-world image enhancement (RUIE) dataset on existing HE[25], CLAHE[26], ICM[27], UCM[28], RGHS[29] and UWCNN[30] methods. The experiments are implemented on i7 processor and Windows 10 Operating System using the MATLAB. The proposed UIETM method is analysed using the natural image quality evaluator (NIQE) [31], UIQM [32] and blind/reference-less image spatial quality evaluator (BRISQUE) [33] evaluation metric.

Evaluation metric

The proposed UIETM method has been analysed using the non-reference evaluation metric. As ground truth information is not available in RUIE dataset. The input of the non-reference evaluation metric is the enhanced image that estimates the quality of the input image. In this paper, three evaluation metrics are used- NIQE, UIQM and BRISQUE.

NIQE [31]: It is based on human vision perception. The lower the NIQE value better isthe image quality. The NIQE is estimated using Eq. 14.

$$D(v_1, v_2, \Sigma_1, \Sigma_2) = \sqrt{(v_1 - v_2)^T \left(\frac{\Sigma_1 + \Sigma_2}{2}\right)^{-1} (v_1 - v_2)} \ldots (14)$$

where v_1, v_2 are mean vector, Σ_1 , Σ_2 are co-variance matrices and the degraded image of the multi-variance Gaussian model.

BRISQUE [32]: It is based on the amount of distortion. It computes the loss of naturalness of the input image. The lower the BRISQUE value better is the image quality. The BRISQUE is computed using Eq 15.

$$\hat{I}(i,j) = \frac{I(1,j) - \mu(i,j)}{\sigma(i,j) + C} \ldots(15)$$

where, I(i, j) is the intensity of the input image, μ(i, j) is the mean, σ(i, j) is the standard deviation and C is constant.

UIQM [33]: It is based on the human vision system perceptiveness. The UIQM is estimated based on three parameters- under-water image colorfulness, sharpness and contrast measure. The higher the UIQM value better is the image quality. The UIQM is estimated using the Eq 16.

$UIQM$ = $c_1 \times UICM$ + $c_2 \times UISM$ + $c_3 \times UIConM$ ....(16)

where, c1, c2 and c3 are the weights.

Testing dataset

The proposed UIETM method is compared and analysed on real-world under- water dataset (RUIE) [34]. The RUIE is collected from real world under-water environment that shows properties of complex under-water environment. The RUIE consists of 4, 230 images. The dataset includes marine animals (such as urchins, scallops) and shows issues (such as color cast, haze, limited lightning). The sample images of the dataset are shown in Fig. 2.

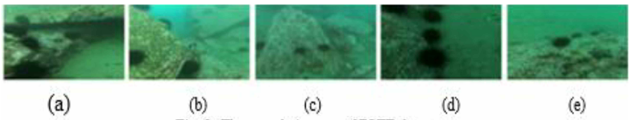


Fig. 2- The sample images of RUIE dataset

Visual analysis

In visual analysis, five real under-water images are used to compare the performance of HE[25], CLAHE[26], ICM[27], UCM[28], RGHS[29], UWCNN[30] and UIETM. The five images are selected based on the degradation level and issues such as color cast, lightning and haze.

Fig.3 shows the comparison of the HE, CLAHE, ICM, UCM, RGHS, UWCNN and UIETM methods. It can be observed that HE removes the color cast but introduce unwanted noise and artifacts. The enhanced images are over-amplified and over-enhanced. As, HE is based on the equalization of the pixel value.

CLAHE is unable to remove the color cast as it dependent on the clip limit. ICM improves the visibility of the degraded image but unable to completely remove the color cast issue. Moreover, some colors are restored as ICM uses contrast stretching issue. On the other hand, UCM improves the quality of the degraded image but partially remove the color cast. Also, real colors of the im- ages are not recovered as it focuses on the saturation and intensity stretching in HSI model. RGHS method works well for nearby objects but unable to completely remove the color cast from the input image. Also, noise is introduced. UWCNN method is able to remove the color cast but introduces yellow color in the enhanced images. The UWCNN is unable to regain the true color of the image. The proposed UIETM method is able to remove the color cast from all the input five images. It can be observed that brightness is improved and the colors are restored. Therefore, the proposed UIETM method works well for color cast and lightning issues.

Quantitative analysis

The quantitative analysis is conducted on first 200 images of the RUIE dataset to analyse theperformance of the proposed UIETM. Fig. 6

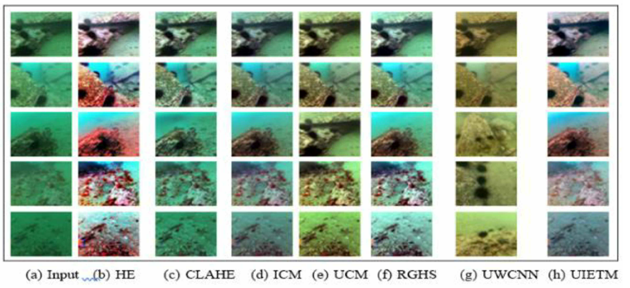


Fig. 3- The qualitative comparison of existing HE, CLAHE, ICM, UCM, RGHS,UWCNN and the proposed UIETM

shows the comparison of the HE[6], HE[25], CLAHE[26], ICM[27], UCM[28], RGHS[29], UWCNN[30] and UIETM methods. The UIETM outperforms all the existing methods in terms of NIQE, BRISQUE, and UIQM.

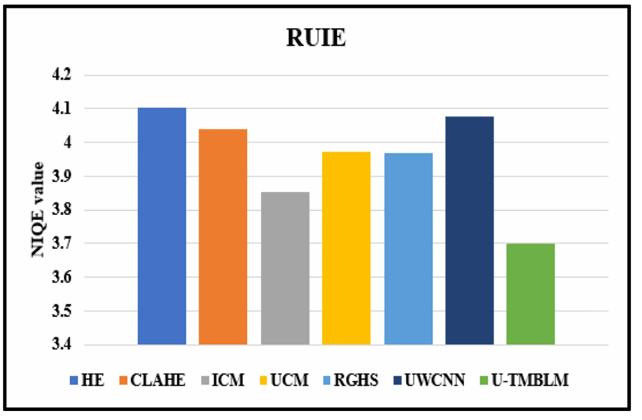


Fig. 4- Comparison of HE, CLAHE, ICM, UCM, RGHS, UWCNN and UIETM on 200 images of RUIE dataset in terms of NIQE.

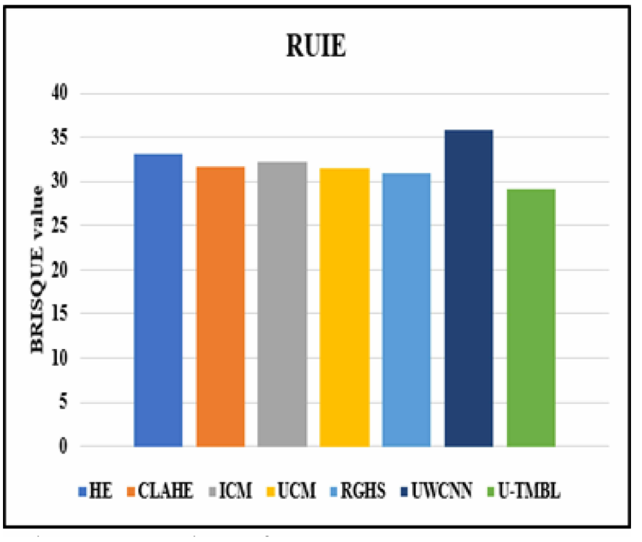


Fig. 5- Comparison of HE, CLAHE, ICM, UCM, RGHS, UWCNN and UIETM on 200 images of RUIE dataset in terms of BRISQUE.

Fig.4 shows that the proposed UIETM obtained the minimum value in terms of NIQE. That implies that the UIETM is able to recover the naturalness of the degraded image. However, HE obtains the highest value because noise is introduced in the enhanced image due to pixel equalization.

Fig.5 shows that the proposed UIETM obtained the lowest value in terms of BRISQUE. That proves that UIETM is able to recover the image as per human visual system. Also, real color is recovered. However, HE obtains the highest value because it equalizes the intensity value.

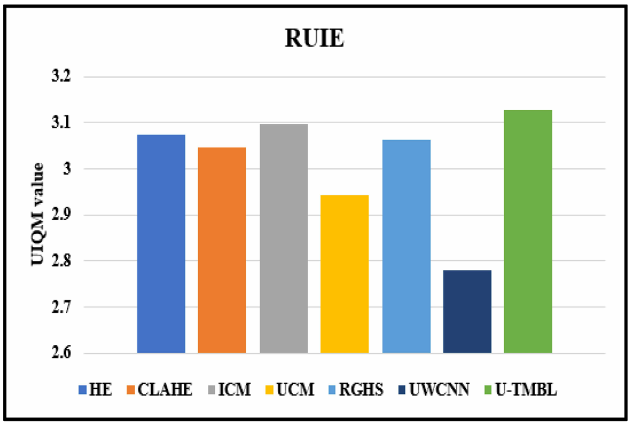


Fig. 6- Quantitative comparison of UIETM with HE, CLHAE, ICM, UCM and RGHS.

Fig. 6 shows that the UIETM method obtained highest value. This implies that the enhanced well in terms of color, contrast and sharpness. Whereas, UWCNN obtained minimum value as the training of the network does not con- siders real underwater images. Moreover, the deep neural networks highly rely on the training dataset and the hyper-parameters.

Conclusion

In the paper, UIETM is presented based on modified transmission estimation. The qualitative and quantitative results shows that the UIETM method over- comes the issue of color-cast and low-lightning.

Furthermore, the existing HE, CLAHE, ICM, UCM, RGHS and UWCNN are compared with UIETM method. The results prove that the UIETM can successfully remove color cast and shows more appealing qualitative results. The quantitative results demonstrates that the UIETM works well in terms of UIQM, NIQE and BRISQUE. However, in the qualitative results it can be observed that the partial blue color cast is still observed. In future, the focus will be on completely removal of color cast from the input image.

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