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CONVOLUTIONAL NEURAL NETWORK BASED DUAL DEEP NETWORK METHOD FOR PERCEIVED DETAILS OF IMAGE AND ASGA METHOD FOR COLOR CORRECTION OF UNDERWATER IMAGE ENHANCEMENT

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Abstract: Underwater images are causing from lightning and illumination problems. Color cast and concentrated noise is a big problem in underwater images. Traditional underwater image enhancement methods are fails to rectify these problems. For that, this work proposed Dual Deep Network method based on the Convolutional Neural Network to enhance the blurred underwater images. Reduces the color cast problems using Underwater White Balance method with color correction method of Adaptive Shades of Gray Assumption. The experimental results show that the proposed method based on the CNN has more competent and effectively enhance the underwater image than traditional State of art methods in terms of PSNR, SSIM, UCIQ and PCQI metrics.

Keywords: Degraded Image, Transmission Map, Scene Radiance, Image Fusion, Color Correction.

I. INTRODUCTION

Underwater image enhancement is used on so many fields such as archaeology, underwater robotics science and biology. It's also used for scrutinize the infrastructure of sea surfaces and underground. In image processing, so many enhancement methods are used to enhance the degraded underwater images but which leads too many color cast problems and illumination problems on the image instead of traditional enhancement method, using CNN based enhancement methods are used to reduce the artifacts caused by color correction and contrast enhancement methods [1].

In the field of oceanography, flooded condition is a big problem to capture a clear picture under the ocean. The tiny mineral particles are diluted in underwater so oceanography researchers cannot capture the mini creature's larva on algae. The algae's are hiding the rocks and tiny living things in under the ocean. For that, underwater enhancement and restoration methods are used to enhance the images from degraded image. The existing methods are need expensive hardware and software equipments and also which didn't refer the details of water depth, types of underwater, seabed types [2].

The image enhancement and restoration methods are based on the modal-free, modal based and data-driven methods. The restoration methods are complicated when comparing to enhancement methods. Restoration methods only focused on the disruption pixels so it's complicated and leads to color artifacts problems. Enhancement methods are considers only replace the good pixels instead of disruption pixel. The data-driven method as like as cnn based methods are provides the good results on underwater degraded image [3] and [6].

This work is formatted as follows: Section I introduce the importance of the Image Enhancement. Section II describes related research works of the Image Enhancement techniques. In the section III represent the proposed methodology. Section IV shows the experimental results and discussion of proposed work. Finally, Section V describes about the conclusion and future work.

II.RELATED WORKS

Fenglei Han et al., [1] proposed the Underwater Image Processing and Object Detection Based on Deep CNN Method for underwater image enhancement. This method is only suitable for robotics methods for underwater object detection but it's not suitable for other types of datasets and dropout layers with some other technologies also is not applicable in this model. When this model is reconstructs by some complicated neural network algorithms only possible to be effective on other types of applications.

Zeba Patel et al., [7] represented the Framework for Underwater Image Enhancement. Here, color balance and fusion methods are used to enhance the underwater degraded images. Edge sharpening and color balancing is used to reduce the color artifacts to improve the quality of degraded underwater images but this method fails to update the clear-cut images when consistency noise contained underwater images and different levels of turbidity underwater images. Computational cost also little high.

Weidong Zhang et al., [9] proposed the method of Enhancing underwater image via Color Correction and Bi-interval contrast enhancement (CCBCE) for improve the quality underwater images. Optimal histogram equalization and contrast enhancement methods are used to highlight the details of low frequency components and sharpening the low frequency edge preserved the details of the underwater degraded image. In this method is not applicable for concentrated noise contained underwater images. This method fails to update the clear background details of underwater degraded image.

Farong Gao et al., [15] referred the method of Underwater Image Enhancement Based on Local Contrast Correction and Multi-Scale Fusion for low contrast underwater images. Here, improved old global method with Multi-Scale Fusion strategy is used to rectify the color distortion problems on underwater image. This method is fails to update the clear background of underwater images.

Xiaoyan Lei et al., [19] proposed the method of A Novel Intelligent Underwater Image Enhancement Method via Color Correction and Contrast Stretching for enhancing the degraded low illumination images. Here, compensation factor is used for color channel or color cast problems to compensate the color distortion problems. Multi-scale convolution is also used to correct the color with local and global stretching problems. Finally, low and poor contrast images and over saturated images are clearly updated by this mechanism. This method is fails to update the three channels over color attenuation problem arises underwater images.

Yidan Liu et al., [21] introduced the method of An Underwater Image Enhancement Method for Different Illumination Conditions Based on Color Tone Correction and Fusion-Based

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Descattering for overcoming the color distortion problems in underwater images. Here, the method is used for only shallow water and depth or deep sea water conditions image problems. Color tone correction module is used to overcome the color tone deviation problems and second module is used for solve the low contrast and pixel wise color deviation problems arises in underwater images. But this method fails to update the minimal color distortion has underwater images.

III. UNDERWATER IMAGE ENHANCEMENT

3.1 Image Optical Method (IOM)

In Underwater Image Processing, capturing the picture has been separated two parts. One is scene radiance caused by light absorption and scattering of underwater suspended water particles. Other part is ambient light transmission occurred by ambient light reflection into the camera by water particles so removing those light illumination problems here using Image Optical Model [22] can be expressed as,

$$I_c(x) = J_c(x)t_c(x) + B_c\left(1 - t_c(x)\right), c \in \{R, G, B\} \quad (1)$$

Here, x indicates a pixel value in the underwater image and c indicates the RGB Color channels, $I_c(x$c indicates is the original image, $J_c(x)$ is indicates the scene radiance, B_c is the Background light, and $t_c(x)$ is the Transmission map for residual energy ratio of the scene radiance reaching the camera. The patch transmission as $\tilde{t}(x)$. The red color more attenuated than green and blue then compare the maximum intensity values of red color to green and blue channels. The min operation in the local patch on the degraded imaging function for transmission can be expressed as [22],

$$\min\left(I_c(x)\right) = \tilde{t}_c(x)_{y\in\Omega(x)}^{min}(J_c(x)) + I(1 - \tilde{t}(x))B_c \quad (2)$$

Here, B_c is denoted as background light. Once again performing min operation for over all three RGB colors can be expressed as,

$$^{min}_{\ \ c}\ {}^{\ min}_{y\in\Omega(x)}\left(\frac{I_c(x)}{B_c}\right) = \tilde{t}_c(x)\ ^{min}_{\ \ c}\ {}^{\ min}_{y\in\Omega(x)}(J_c(x)) + I(1 - \tilde{t}(x))\tilde{t}_c(x) \quad (3)$$

Next, calculate all over the local min brightest pixel value corresponds to the Background light B_c can be expressed as [1],

$$B_{c=}{}^{max}_{x\in i}\ {}^{\ min}_{y\in\Omega(x)}\ I_c(y) \quad (4)$$

Here, $I_c(y)$ is the local color components of original image in each patch. Finally, the scene radiance is updated according to the transmission depth map. The predicted depth map is $d_{x.}$ The TM for filtered image calculated by using,

$$t^r(x) = e^{-\beta^r}d(x) \quad (5)$$

The transmission of t(x) is set to $t_0 = 0$, that means remaining parts of any haze preserved in deep depth regions so for that final scene radiance can be expressed as [14] and [4],

$$J(x) = \frac{I_c(x) - B_c}{\max\left(t(x), t_0\right)} + B_c \quad (6)$$

Here, a typical value of t_0 is 0.1. The received image will be too dark and color distortion

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problems so for that applying BLTN method to recover the image.

3.2 Filtering Technique

Underwater image contains the darkest regions by shadows and lightning conditions with color distortions. The image edges are hiding by image darkness so the median filter is used to remove the edge related noise from underwater degraded image. The median filter is an edge-preserved filter. It's smoothing the edge regions and applies the center pixel intensity value of median value to neighborhood pixels for finds out the discontinuities in the nearest pixels can be expressed as,

$$y[m, n] = median\{x(i, j), (i, j)\epsilon w\} \quad (7)$$

Here, m, n represents a coordinate pixel values and w denotes a neighborhood pixel intensity value. The eq. (6) is modified to apply on transmission map problem for captured the image (original image) is directly apply on the smoothed transmission of $\tilde{t}_{(x)}$ can be expressed as,

$$\tilde{t}_{(x)} = 1 - \min_{c}\left(\underset{y\epsilon\Omega(x)}{median} \frac{I_{c(y)}}{B_c}\right) \quad (8)$$

Finally, the filtered image processed in two ways. First way is applying underwater white Balance (UWB) with color correction method of (ASGA) on filtered image and another one is finds out the transmission maps and background light estimation by using BLTN method to rectifying the color distortion problems and edge preserved problems in filtered image.

3.3 Underwater White Balance (UWB)

The proposed methodology is employs three stages. The first stage is color correction of underwater filtered image. UWB [16] method applies to remove the remaining color cast problems in filtered image and which improves the image quality by removing other color cast problems. The red color is disappeared at 5m depth in underwater so red color cast problems are rectified by using WB method in four steps as follows:

1. The Green color wavelength is shorter so it's goes to disappear in deeper underwater depth. Then blue wavelength is lightweight so it's goes very deeper into the underwater depth so which affects the true color of underwater images.
2. Green channels only provide the clear high accuracy results and background of the image is visually cleared so compensate the red channel, which green channel partly added to the red ones to get more accuracy results.
3. The mean values of red and green differentiation is proportional to the compensation values made.
4. The WB method performing red channel compensation to avoid the red channel saturation. The red channel pixel values are already significant so it's could not be changed. While, the green channel is added to red channel is not significant which leads to overexposure regions. The filtered image region would be more attenuated so overcome this problem we using Adaptive Shades of Gray Assumption (ASGA) color correction method.

3.4 Adaptive Shades of Gray Assumption (ASGA)

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The color correction method of ASGA is used for removes the color artifact arises by WB method. Here, Max-RGB is combined to original shades of gray to get ASGA method to overcome the color distortion problems in preprocessed image and identifies the color illumination by using color temperature. The original Max-RGB can be expressed as [1],

$$\max_{i\in\{1,2....N\}} R_i = \int_\omega E(\lambda)R(\lambda)d\lambda = R_e$$

$$\max_{i\in\{1,2....N\}} G_i = \int_\omega E(\lambda)G(\lambda)d\lambda = G_e$$

$$\max_{i\in\{1,2....N\}} B_i = \int_\omega E(\lambda)B(\lambda)d\lambda = B_e \tag{9}$$

Here, $E(\lambda)$ denotes a Spectral distribution, $S(\lambda)$ is *Lambertian* surface and, $C\lambda$ is a Color signal of RGB Colors. The original shades of gray can be assuming in average of pixels raised to the power of p can be expressed as,

$$R_{p,i=} \int_\omega \{E(\lambda)\}^p\ s_i(\lambda)\}^p\ R(\lambda)d\lambda \tag{10}$$

Here, the red color channel formula as like as applied for green and blue channels in same way. The Shades of Gray Assumption can be expressed as,

$$\mu_p\big(s(\lambda)\big) = \left[\sum_{i=1}^{N} \frac{\{s_i(\lambda)\}^p}{N}\right]^{1/p} = k_p \tag{11}$$

Here, Max-RGB and Shades of Gray combined to produce Adaptive Shades of Gray Assumption for the Pre processed image can be expressed as,

$$I(x) = \int_\omega E(\lambda)\, S(\lambda, x) C(\lambda) d\lambda \tag{12}$$

Here, $I(x)$ denotes to preprocessed image, $E(\lambda)$ is the radiance from source of light, (λ) is the wavelength of colors, $S(\lambda, x)$ is the surface reflectance, $C(\lambda)$ denotes the sensors sensitivity and ω is the visible spectrum. Removing the weak illumination from entire image and the average color is raised to power of n according to the shades of gray and Max-RGB can be expressed as,

$$ke = \left[\frac{\int I^n dx}{\int dx}\right]^{1/n} \tag{13}$$

And Max-RGB

$$ke = max I(x) * \left[\frac{\int I^n dx}{\int dx}\right]^{1/n} \tag{14}$$

Here, k is a constant value and e is a illumination. $I(x)$ is a preprocessed image and n set the default value of n=6. Maybe n take any number from 1 to infinity. Calculate the illumination after that applying WB method to remove red artifacts. Finally, the color corrected image is updated.

IV. PROPOSED METHODOLOGY

The proposed work consists of three stages shown in Fig.3.1.First one is Color Correction, Next one is Dual Deep Network (DDN) based on the Convolutional Neural Network (CNN) method for refine the underwater image edges. Third one is Adaptive Multi-

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Scale Fusion (AMSF) [7] method is used for fuse the color corrected image and DDN image to produce the enhanced underwater image. In preprocessing step, the median filter is applied for remove the noise from underwater degraded image [14].

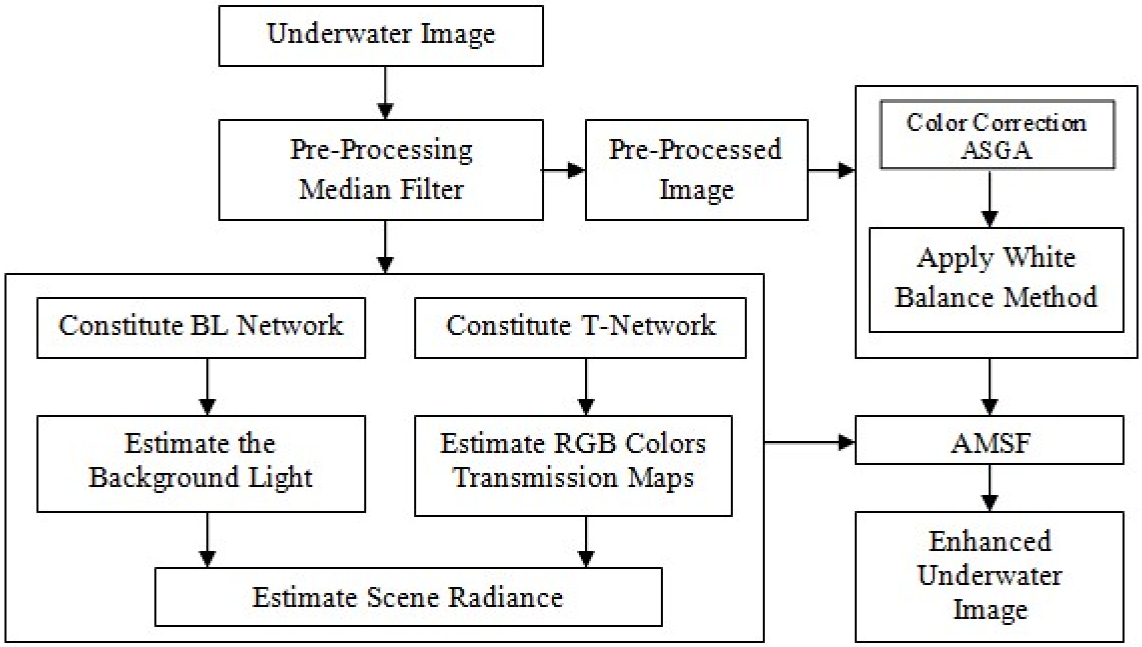

Fig.3.1. Block diagram of proposed DDN method

Here Dual Deep Network contains two networks one is Transmission Map network and another one is BL network method applied for calculating the background light for difficult light-particle interplays[14].Scene Radiance map is based on the IOM [22] method is used for calculate the radiance of combined Background Light of R and Transmission network method. The Underwater White Balance (UWB) [16] and Adaptive Shades of Gray [1] methods are used to remove the color distortion problems.

4.1 Dual Deep Network (DDN)

The proposed methodology of DDN method is based on the Convolutional Neural Network (CNN) to refine the transmission maps of filtered image and calculate the background light for removing light attenuation problems. Estimate the scene radiance according to Image Optical Model (IOM) [22]. The Underwater blurred image is select from UIEBD [23] dataset which images are well trained synthesized images.

The median filter used to finds outs the edge regions and noise occurred only at neighborhood pixels. So the blurred deep regions and blurred part of the image background problems are recover to using DDN method. It consists of two deep networks as follows:

1. The Noise free image moved to Background Light (BL) Network to calculate the three colors of B_r:B_g:B_b for perceives out the scene radiance map.
2. The Transmission network consists for clarify the filtered image region edges by estimating transmission maps via equation (5). The three RGB colors transmission maps are calculated to add with the Background Light transmission to get the scene radiance of enhanced image.

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Finally, the enhanced image is updated by adding the R network and Transmission maps network to scene radiance. The proposed method algorithm is shown below.

a) Background Light Network (BL-Network)

BL network is used for depicting between filtered image and its corresponding Background light. The simple and sophisticated structure of BL network is used to calculate the different lighting conditions at different depths of underwater filtered image according to RGB colors wavelengths. The BL network mainly contains two operations such as convolutional layer with max-pooling.

The BL network structure contained five convolutional layers. The first three layers are con layers with filters. The filters sizes are 5x5, 5x5, and 3x3. The next two layers are Max-pooling layers and normalization layer which has sizes are 2x2 and 2x2. The last two layers are fully connected. The final output of Background Light threshold range is [0, 1].

b) Transmission Network (T Network)

T network estimate the transmission maps of RGB colors and foretell the scene depth. The multi-scale based two architecture networks made the transmission network. First one is depth network, which used to finds out the depth of the filtered image. Another one is filtered network also used for refine the transmission maps according to scene depth.

The depth network consists by six conv layers from that first two layers are pooling layer and another one is normalization layer. The three layers are fully connected layers which depth output is added to the first layer of filtered network. The filtered network has four conv layers and four upsampling layer. The upsampling layer is added to the before last conv layer for finds out the refinement of upsampled feature map. The predicted depth map is d_x. The TM for filtered image calculated by using,

$$t^r(x) = e^{-\beta^r} d(x) \tag{14}$$

Here, β^r is the attenuation coefficient value of red channel. Further, green and blue color attenuation coefficients computed by using,

$$t^k(x) = t^r(x)\frac{\beta^k}{\beta^r}, k \in \{g, b\} \tag{15}$$

Finally, the scene radiance of the enhanced image updated by combined the BL estimation and Transmission maps calculation of three RGB colors to produce the scene radiance of enhanced image can be expressed by,

$$J(x) = \frac{I_c(x) - B_c}{\max(t(x), t_0)} + B_c \tag{16}$$

The scene radiance of enhanced image and color corrected image fused by AMSF method.

V. FUSION PROCESS

5.1Adaptive Multi Scale Fusion (AMSF)

The third stage of proposed methodology is Adaptive Multi Scale Fusion (AMSF) is used for fused the color corrected image and DDN based Scene Radiance calculated image to

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produce the final enhancement underwater image Inspired by Linfeng Bai [6]. The fusion method needs to calculate the weight maps of input images to produce clear enhanced image. Weight maps are based on the image quality or saliency metrics. Three weight maps are calculated for two input images such as follows.

a) Laplacian contrast weight (WL)

Estimates the luminance of each input channel for global contrast by computing the original value of Laplacian filter but in underwater image processing task, this weight measure is not enough for this reason of its cannot vary the difference between the ramp and flat regions of the underwater image. To operate this problem, here introducing next contrast calculation based weight measure.

b) Saliency Weight (WS)

Compute the saliency level of underwater scene when the underwater salient object loss its important accent in the underwater image. This algorithm is made by the biological contents of center-surrounded contrast. The saliency map only produces the high values of luminance and foreground areas of regions. So overcome this problem here using another weight measure.

c) Saturation weight (WSw)

Here, used the fusion algorithm for deeply saturated regions chromatic information. This weight measurement computes the each input I_k deviation for each and every location of pixel value between R_k, G_k and B_k with the luminance of L_k of the k^{th} input can be expressed by,

$$W_{Sat} = \sqrt{1/3\left[(R_k - L_k)^2 + (G_k - L_k)^2 + (B_k - L_k)^2\right]} \tag{17}$$

Practically, for the two inputs, the 3 weight maps are combined into single weight map such as follows. W_k is obtained by summing the W_L, W_S and W_{sw} weight maps. The K combined maps are after this normalized on a pixel by pixel basis thorough divide by the weight of each pixel in each map by the sum of the weights of the same pixel for over all maps. Finally, the normalized weight maps of W_k is computed by using,

$$\bar{w}_k = (W_k + \delta)/(\textstyle\sum_{k=1}^{K} W_k + K.\delta) \tag{18}$$

Here, δ denotes the small normalization term and set to 0.1 which ensures the each input put up with the corresponding output.

Adaptive Multi-Scale Fusion Process

The AMSF process is based on the Laplacian Pyramid decompose the image into a sum of band pass images. In each level of the pyramid filter the image using the filter of Gaussian kernel G, and decimates the image by factor of 2 in both directions. To *Gl* denote the continuation of *l* low-pass filtering and decimation which is followed by *l* up-sampling operations. Here define the N levels of L*l* pyramids can be expressed by,

$$= \sum_{l=1}^{N} L_l\{I(x)\} \tag{19}$$

Here, L_l and G_l describe the *l*th level of the Laplacian and Gaussian pyramid, respectively. Both pyramids have the equal number of levels and also which is mixing the

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Laplacian inputs with the Normalized Weights are performed separately at its respected levels of *l* can be expressed by,

$$\mathcal{R}_l(x) = \sum_{k=1}^{K} G_l\left\{\bar{W}_k(x)\right\} L_l\left\{I_k(x)\right\}$$

(20)

Here, *l* represents the pyramid levels and *k* denotes the no. of input images and practically N depends on the image size, which has a direct effect of the degraded image. The final output of fused image of underwater enhanced image is updated successfully. The DDN algorithm is shown below.

DDN Algortithm

Input Image : *Underwater Degraded Image*

Output Image : *Recovered Image*

Step 1: Select the single image from underwater image dataset.

Step 2: In pre - processing step, the median filter is applied to remove region edge noise from underwater degraded image calculated by using,

$$\tilde{t}_{(x)} = 1 - \min_c\left(\operatorname*{median}_{y\epsilon\Omega(x)} \frac{I_{c(y)}}{B_c}\right)$$

Step 3: UWB method is applied for removing color distortion of red color problems in Filtered image.

Step 4: ASGA is applied to remove the remaining color cast problems on white balanced image calculated by using,

$$ke = \left[\frac{\int I^n dx}{\int dx}\right]^{1/n}$$

Step 5: DDN method consist of two networks for enhance the underwater image such as R network and T network.

Step 6: Constitute of BL Network is used for calculate the different depth based lightening problems on underwater image and also removing the different illumination problems.

Step 7: T Network is used for refine the transmission edges of RGB colors by using Transmission Network calculated by using,

$$t^r(x) = e^{-\beta^r} d(x)$$

Step 8: The enhanced scene radiance of image is updated by combine the R of background light and TN is calculated by using ,

$$J(x) = \frac{I_c(x) - B_c}{\max\,(t(x), t_0)} + B_c$$

Step 9: Finally, Adaptive Multi Scale Fusion method is used for update the final result of enhanced image by fuse the color correction image and scene radiance of DDN image calculated by using,

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$$\mathcal{R}_l(x) = \sum_{k=1}^{K} G_l\left\{\bar{W}_k(x)\right\} L_l\left\{I_k(x)\right\}$$

Step 10: The enhanced recovered image is finally updated.

VI. RESULTS AND DISCUSSIONS

6.1 Performance Metrics

The following metrics are used to evaluate the proposed method with experimenting on different underwater images. Underwater degraded images are select from the UIEBD [23] trained synthesized underwater dataset.

a) Peak Signal to Noise Ratio (PSNR)

It has simple and graceful structure and easy to handle and which has two signal such as normal signal and distortion signal. The normal signal produces the clear signal and the distortion signal produce error signal. It's evaluated from MSE metric and improves the image visual quality calculated by using,

$$PSNR = 10log_{10}\frac{L^2}{MSE} \tag{21}$$

b) Structural SIMilarity Index (SSIM)

It has simple *x* and *y* image patches of two different images located at two different locations. Then which have three measurements such as luminance $l(x, y)$, Saturation $s(x, y)$ and Chrominance $c(x, y)$ for improve the image perception quality. Then it has used the some statistical calculation can be expressed by,

$$\begin{aligned}\text{SSIM} &= l(x, y) \cdot c(x, y) \cdot s(x, y), \\ &= \left(\frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}\right)\left(\frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}\right)\left(\frac{\sigma_{xy} + C_3}{\sigma_x + \sigma_y + C_3}\right)\end{aligned} \tag{22}$$

Here, μ_x and μ_y are represents the *x* and *y* image patches and σ_x, σ_y represents the standard deviations of *x* and *y*. σ_{xy} is represents the cross correlations of x and y patches of when removing the noise from image. Where avoids the zero divisions here using C_1, C_2 and C_3 constants.

b) Underwater Color Image Quality Evaluator (UCIQE)

It's consists by saturation, chroma and contrast based on the CIELab color space for expose the underwater image quality. It's can be expressed as,

$$\text{UCIQE} = c_1 \times \sigma_c + c_2 \times con_l + c_3 \times \mu_s \tag{23}$$

Here, σ_c and con_l represents the standard deviation of chroma, contrast of the luminance. μ_s denotes the mean value of saturation. The important thing is human visual is notified here so the human visual is correlation with the variance of chroma.

c) Patch-based Contrast Quality Index (PCQI)

It's opposed on the global statistics. It's utilized three characteristics or units such as mean, signal strength and structure which can be expressed as,

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$$\mathrm{PCQI} = q_i(x, y) \cdot q_c(x, y) \cdot q_s(x, y) \tag{24}$$

Here, $q_i(x,y)$ denotes the mean intensity and $q_c(x,y)$ denotes the contrast changes in pixels. $q_s(x,y)$ Represent the any distortion in structural. But it's little expensive when compared with other metrics. In fig 4.1 shows the visual analysis of underwater images, which taken from UIEBD [23] dataset and compare with the existing methods of CCBCE and ALTN by the proposed method of DDN to produce the effective results than existing methods. The table 6.1 shows the performance evaluation of the proposed method produce the excellent results on underwater images than existing method.

Table.6.1 Performance Evaluation of Proposed Method for Rock Image

Method	PSNR	SSIM	UCIQE	PCQI
CCBCE	18.723	0.679	0.570	1.162
ALTN	19.113	0.683	0.593	1.174
DDN	21.143	0.690	0.605	1.184

The table 6.1 shows DDN has better performance in terms of PSNR, SSIM, UCIQ and PCQI than CCBCE and ALTN on Underwater Image.

Table.6.2 Performance Evaluation of Proposed Method for Reef Image

Method	PSNR	SSIM	UCIQE	PCQI
CCBCE	19.593	0.673	0.572	1.159
ALTN	20.105	0.686	0.595	1.165
DDN	22.126	0.691	0.612	1.179

The table 6.2 shows DDN has better performance in terms of PSNR, SSIM, UCIQ and PCQI than CCBCE and ALTN on Underwater Image.

Table.6.3 Performance Evaluation of Proposed Method for Coral Reef Image

Method	PSNR	SSIM	UCIQE	PCQI
CCBCE	21.593	0.676	0.589	1.168
ALTN	22.123	0.684	0.598	1.173
DDN	23.143	0.693	0.614	1.181

The table 6.3 shows DDN has better performance in terms of PSNR, SSIM, UCIQ and PCQI than CCBCE and ALTN on Underwater Image.

VISUAL ANALYSIS

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Fig 6.1. The Visual Analysis for an underwater image

VII. CONCLUSION

The proposed DDN method based on the CNN functionally cope-with color cast and color distortion problems on underwater images. Here, color corrected image and DDN based Scene Radiance calculated image fused to produce the better clear images than existing methods. The experiments results are shown the DDN has able to enhance the wide range of underwater images (e.g. distinct cameras, light positions, and depth) with higher accuracy in terms of PSNR, SSIM, PCQI and UCQI than existing methods. Hence, the proposed method is more suitable for underwater image enhancement.

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