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Colour Balancing with Average Filtering and Principle Component Analysis for Underwater Images/Video Enhancement

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Abstract *- Underwater video and imagery play a vital role in collecting and analyzing underwater information. Quality images and videos can provide accurate information for underwater systems. Quality images and videos can provide accurate information for underwater systems. Unfortunately, underwater images are responsible for low resolution, color shades, blurring, low-light exposure, and irregular illumination, which severely impacts the detection and analysis of underwater data. In order to enhance images obtained underwater, there are various methods have been developed. In this paper, we propose a new underwater image enhancement model that consists of four steps, namely: color correction, YUV channel decomposition, improving Y channel, and creation of the final image. The first step involves the color correction of the original image. In the second step, this color image is transformed into YUV space, and the luminance component is refined. The third step makes use of average filtering and histogram equalization along with principal component analysis. Finally, underwater images are obtained by transforming YUV color space into RGB color space. To enhance underwater videos, source data are decomposed into frames that are enhanced using the proposed methodology. The experimental analysis indicates that the proposed model outperforms other state-of-art methods*

Keywords *- Underwater video/image enhancement, color balancing, color channel decomposition, average filtering (AvgFil.), histogram equalization (Heq.), principle component analysis (PCA).*

I. INTRODUCTION

Underwater imaging has numerous drawbacks due to its peculiar physical properties [1] [2]. Underwater images are of low clarity due to the attenuation of the light they transmit[3]. The light attenuates significantly with the distance and depth mostly because of the various factors that introduce attenuation into light radiation [4] [5]. Absorption reduces the amount of light, while scattering is what causes the light direction to change [6]. These properties of the underwater environment limit the access to far-off objects and thus resulting in blur image [7] [8], [9]. Basically, in seawater, the objects at a range of more than 10 meters are almost blurred, and the details are darkened because they have been diminished by the water depth [10] [11]. There have been many measures to recover and improve deteriorated images, with little success [12]. The primary difficulty is using multiple images, specialized hardware, and using polarization filters to overcome the problem. Hsieh et al. [13] suggested the appropriate dark channel prior (DCP) for the single image deburring. According to this algorithm, an ideal haze-free image has relatively low channel strength in its dark channel. In [14], a contextual regulation method was evaluated that concluded optimistic assumption of transmission. In [15] non local image dehazing (NLP) is proposed. The basic idea of the proposed technique relies on the assumption that an image can be effectively depicted with less than several hundreds of different colors. This corresponds to several hundred tight color clusters. In [16] proposed method make contributions in both measurement of haze and identification of defects in images. First, an image-guided, depth-edge-aware smoothing algorithm is implemented to correct an inaccurate atmospheric transmission map. Then Gradient Residual Minimization (GRM) is utilized for the recovery of the image while suppressing potential visual artifacts. In [17] color balancing with image fusion is proposed for underwater image enhancement (CBUE). The proposed approach merge two image that are extracted from a color-corrected and white-balanced version of a source images. In [18] in order to satisfy technical constraints of an underwater medium method based on LAB color channel correction is proposed (EUIV). This technique distinguishes two color-corrected images that display better underwater scene and also calculate weight maps that attempt to improve the transparency of objects at great distances which are effected due to the medium scattering and absorption.

This paper proposes a method to enhance underwater video and images. The proposed method makes use of color channels, image decomposition, and color balancing schemes to generate enhanced results.

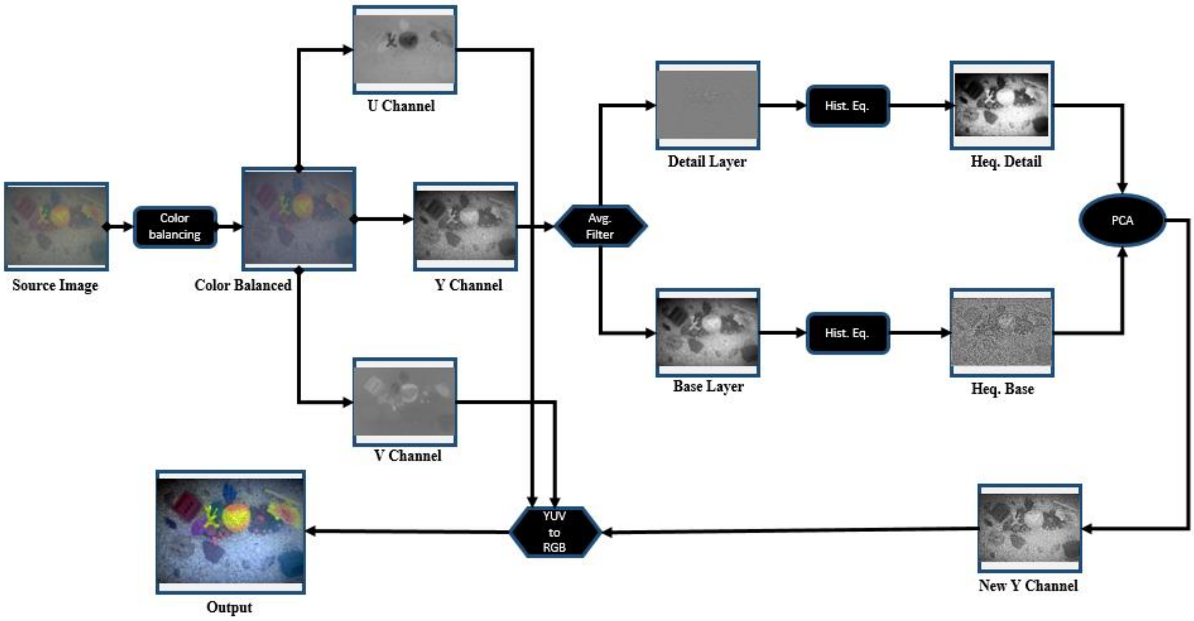

Fig. 1. Proposed Methodology

II. PROPOSED METHODOLOGY

This paper introduces a novel underwater image enhancement model. The proposed method mainly consists of four steps that are color correction, YUV channel decomposition, improving Y channel, and construction of the final image, as shown in Fig. 1. The first step of the proposed method is the color balancing of the original image. In the second step, this color-balanced RGB image is transformed into YUV image space, and the luminance (Y) channel is processed for refinement. The third step makes use of average filtering and histogram equalization along with principal component analysis. Finally, in the fourth step, enhanced underwater images are obtained by converting YUV color space into RGB color space. For underwater video enhancement, source videos are decomposed into frames, and each frame is improved using the proposed methodology. Furthermore, these processed frames are combined together to provide enhanced underwater videos. The details of the proposed framework are described below.

A. Color balancing

White balancing is a technique aimed at obtaining the most accurate colors for the images without unnecessary color casts resulting from different illuminants [17]. White balance in under 30-feet water experiences significant color variations due to the non-linearity of the visual spectrum. Taking into consideration the available white balancing strategies, we found a suitable approach to our problem. In our experiment, we used the white balancing solution derived from Cosmin et al. [17]. Therefore, the illumination is determined by the value χ_I measured, taking into account the average scene χ_{ref} and the transition parameter λ.

$$\chi_I = 0.5 + \lambda\chi_{ref}$$

The average color χ_{ref} has been used to measure the illuminant since the color is determined based on Minkowski norm [17]. The parameter value λ attain visually pleasing results at $\lambda = 2$. This processing technique will eliminate color cast, enhance the truer white color and provide more accurate shades via an image.

In the proposed method, the source images and videos are pre-processed with the white balancing technique in the first stage to enhance the image characteristics.

B. RGB to YUV color space conversion

There are various color space models available for image analysis [19]. Some of the essential techniques are HSV, YUV, LAB, YIQ, etc. Every color space model is important in the field of computer graphics. To increase the contrast between the image and the non-uniformly illumination, it is appropriate to use the YUV color model, as its Y element contains detailed information of luminance component and its U and V components are blue-difference and red-difference color elements [19]. The key benefit of the YUV space model is that we could improve the luminance by enhancing the Y component without affecting the color information in U and V. In the proposed methodology, we transform the white balanced RGB color image into the YUV color space. To transform the RGB color model into a YUV color model, the following equation is used.

$$\begin{pmatrix} Y \\ U \\ V \end{pmatrix} = \begin{pmatrix} 16 \\ 128 \\ 128 \end{pmatrix} + \mu \cdot \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

Where,

$$\mu = \begin{pmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.000 \\ 112.000 & -93.786 & -18.241 \end{pmatrix}$$

And $Y: [a, b], U: [a, c], V: [a, c]$

Where a, b, c are 16,235 and 240.

C. Decomposition of Y channel and contrast enhancement.

Once we obtain the Y channel of a color-balanced RGB image, we use an average filter [20] such that the Y channel is decomposed into its base layer and information layer. The base layer is obtained using the average filter as follows:

$$Y_{base} = AvgFil(Y)$$

Here, Y_{base} represents the base layer of the Y channel, and $AvgFil$ represents the average filtering on the Y channel. To evaluate the information layer Y_{detail}, we subtract the base layer Y_{base} from the Y channel. Therefore, the information layer is calculated as:

$$Y_{detail} = Y - Y_{base}$$

The base layer contains the luminance component, and the information layer contains the details of the luminance component.

After the calculation of the base layer and information layer, we used histogram equalization on both extracted layers (base and information) for contrast enhancement. This can be given as:

$$NY_{base} = histeq(Y_{base}),$$
$$NY_{detail} = histeq(Y_{detail}).$$

Where, NY_{base} is the histogram equalized base layer and NY_{detail} is the histogram equalized information layer?

In order to generate a new enhanced Y channel, we used PCA (principal component analysis) based image fusion strategy on NY_{base} and NY_{detail} besides, this can be given as:

$$NY = PCA(NY_{detail}, NY_{base})$$

Fig. 2 shows the (a) white-balanced image, (b)-(d) U, V, Y channels of the white-balanced image, (e), (f) are the extracted base and information layers, (g), (h) are the histogram equalized layers (base and information), (i) is the new obtained Y channel and (j) is the output generated.

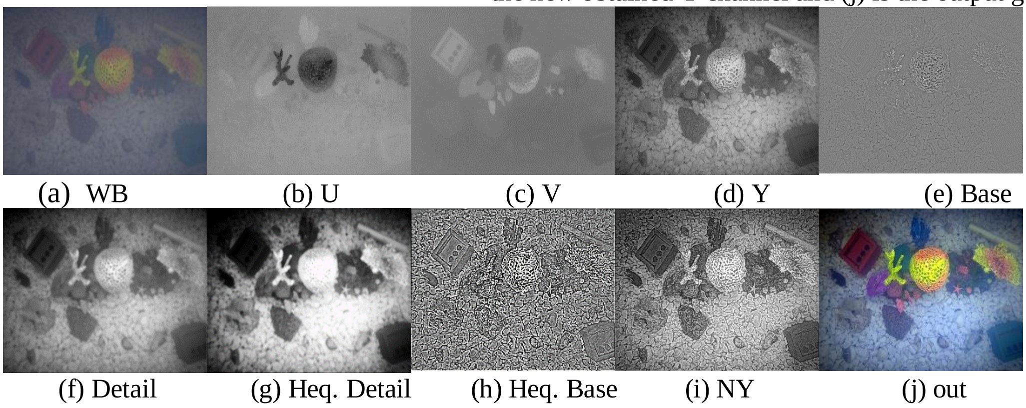

Fig.2. (a) white balanced image, (b)-(d) U, V, Y channels, (e), (f) base and detail layers (g), (h) histogram equalized layers (base, detail), (i) new Y channel, (j) output

D. YUV to RGB color space conversion

Finally, we generate the enhanced underwater image by converting NY, U, V into RGB space, and mathematically it can be represented as follows:

$$N_R = 1.64(NY - 16) + 1.596(V - 128)$$
$$N_G = 1.64(NY - 16) - 0.391(U - 128) - 0.183(V - 128)$$
$$N_B = 1.64(NY - 16) + 2.018(U - 128)$$

E. Underwater video enhancement

For underwater video enhancement, first source videos are extracted into frames and step A to D are applied on each frame. Moreover, these enhanced frames are converted back to .mp4 format. In this manner, an enhanced underwater video is generated. For the frame extraction, we use the matlab audio-video toolbox. The processed video with the proposed method will be available on request, and the results obtained are shown in Fig. 5.

III. RESULT AND DISCUSSION

A. Experimental setup

The proposed underwater image enhancement technique is compared with five other existing methodologies to justify its efficiency and effectiveness. The experiments are being conducted on a laptop using Matlab R2016b with an Intel (6th Gen) processor and 4GB of DDR4 RAM. The compared techniques are NLP, RIVD, CBUE, EUIV, and DCP. We choose default parameter settings for the proposed method. For the effectiveness of the proposed method, we have considered the turbid dataset. The analyses from the algorithms are expressed in fig. 3. The results obtained by the proposed method are much precise and consistent in both visual interpretation and analytical evaluation.

B. Subjective evaluation

The visual analysis of the proposed model is compared with NLP, RIVD, CBUE, EUIV, and DCP and shown in fig.3. The findings from the EUIV and CBUE experiment show a great contrast with multilayer properties. However, these images reflect wide-ranging colors. The images produced by NLP and RIVD are not blurred by illumination distortion; moreover, the change, in contrast, is not significant, whereas the detail obtained by DCP is substantially blurred. The methodology proposed in this paper provides the best results in terms of color and visual appearance.

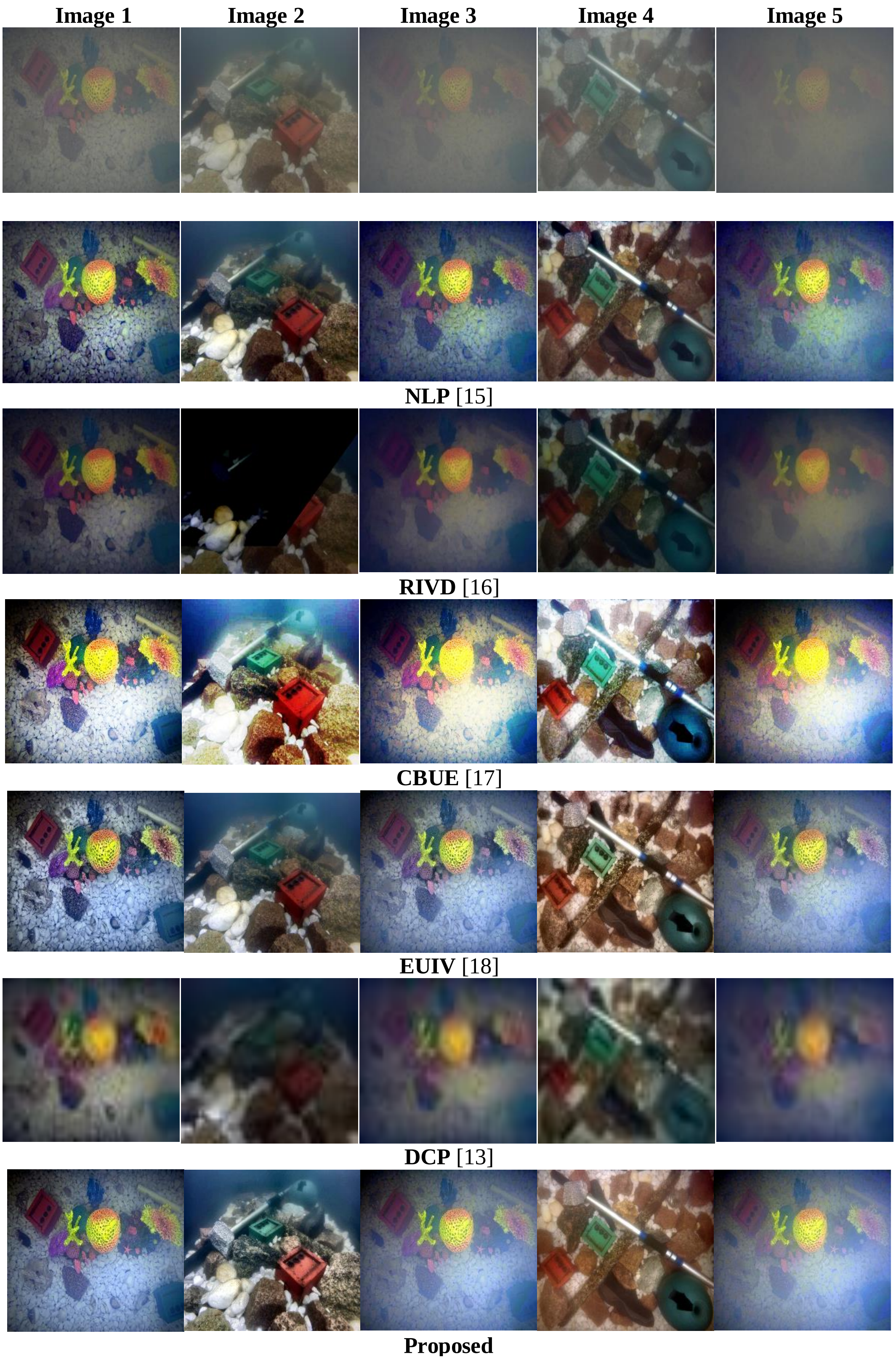

Fig. 3. Visual results for proposed and state-of-the-art methods

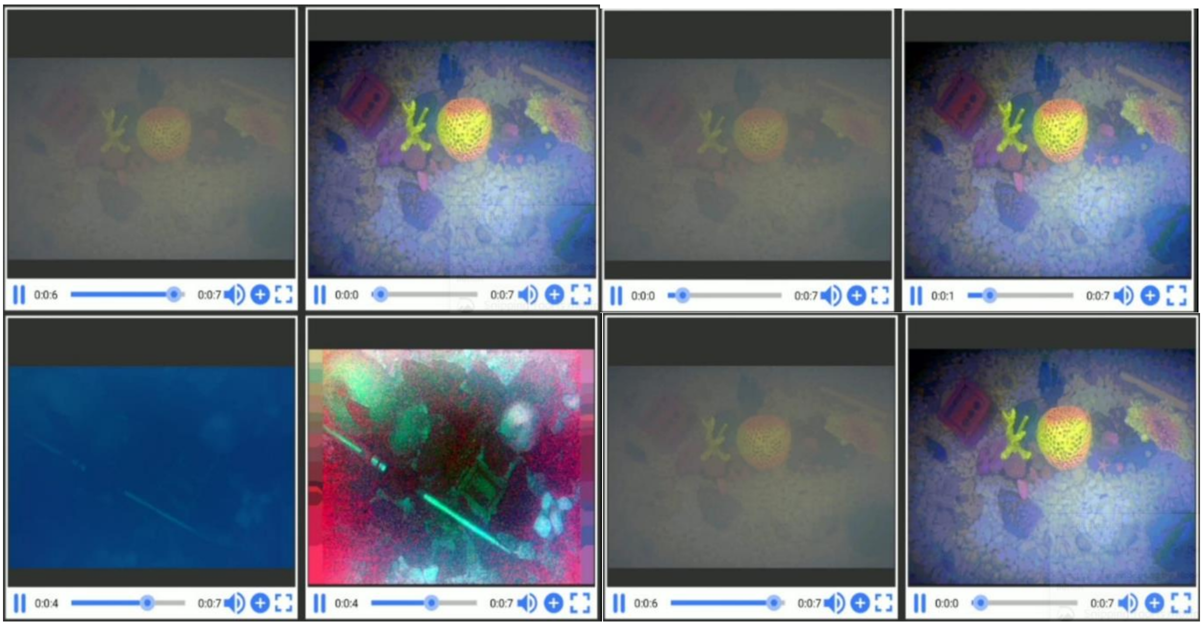

Fig. 4. Underwater video enhancement by the proposed model

C. Objective evaluation

To assess the effectiveness of the proposed model, we choose four metrics, namely: mean square error (MSE), peak signal to noise ratio (PSNR), structure similarity index (SSI), and structural content (SC). The overview and the prescribed metrics are as follows:

D. Mean square error (MSE)

MSE tests the amount of error between the original and compressed image. A lower MSE value reflects lower error. The notation for MSE is written as follows:

$$MSE = \frac{1}{v}\sum\sum\left(E_{d(i,j)} - O_{d(i,j)}\right)^2$$

Here, v is the image size, O_d display original image and E_d represents edges of the image.

Table 1 provides a contrast between the various methods for MSE values. From table 1, it is clear that the MSE value of the proposed technique is better as compared to other techniques. This shows that the proposed image via the proposed method is more accurate. The representation of table 1 is given by fig.4.

E. Peak signal to noise ratio (PSNR)

PSNR represents the calculation of maximum error, and it is given as:

$$PSNR = 10.\log_{10}\left(\frac{O^2}{MSE}\right)$$

Here, O shows the maximum pixel value of an image.

Table 2 shows the result of PSNR. It is clear from table 2 that the average value of psnr obtained from the proposed method is better compared to other state-of-the-art methods, and it can be seen from fig. 5 as well.

F. Structure similarity index (SSI)

The Structural Similarity Index (SSI) quantifies how much deterioration occurs in an image when its properties are altered by data compression or transmission loss. Mathematically it can be represented as:

$$SSIM(u,v) = \frac{(2\mu_u\mu_y + x_1)(2\sigma_{uv} + x_2)}{({\mu_u}^2 + {\mu_v}^2 + x_1)({\sigma_u}^2 + {\sigma_v}^2 + x_2)}$$

Where, u and v are two windows of size $N \times N$, μ_u, μ_v are average of, u and v, ${\sigma_u}^2, {\sigma_v}^2$ are the variance of u and v, σ_{uv} is the covariance of u and v. And x_1, x_2 are variables used to stabilize an expression with an unstable denominator?

The SSIM results obtained from the proposed method compared to other methods are shown in table 3. It is seen from the table that the average value of SSIM obtained via the proposed method outperforms other methods. The observation of table 3 can be seen in fig. 6.

G. Structural content (SC)

The quality metric is expressed as follows:

$$SC = \frac{\sum_{a=1}^{m}\sum_{b=1}^{n}(U_{ab})^2}{\sum_{a=1}^{m}\sum_{b=1}^{n}(V_{ab})^2}$$

Greater the value of SC is a greater indicator of the picture being of low quality.

From table 4, it can be observed that the average value of SC obtained by the proposed method performs better, and the same can be seen in Fig 7.

Table. 1. MSE

Image	NLP	RIVD	CBUE	EUIV	DCP	Proposed
1	1442.0378	2785.192	3908.498	1325.6153	1020.4187	801.2396
2	1400.5987	6243.3725	5665.5633	1608.6461	3096.5493	1143.8244
3	1957.3515	2396.0249	3485.1331	1105.4129	1499.2406	984.8272
4	809.5657	4175.537	3797.8893	2168.5607	1208.4764	1087.2039
5	1669.2727	1601.19023	4723.5575	1157.4726	1636.2914	1215.318

Table 2. psnr

Image	NLP	RIVD	CBUE	EUIV	DCP	Proposed
1	16.5741	13.7153	12.7562	17.4521	18.0761	19.6387
2	17.1678	10.6768	9.9841	16.7464	13.7222	18.2274
3	14.3905	13.5123	13.2088	17.0812	15.5485	17.5829
4	20.3722	13.2476	13.6593	16.2974	18.6323	19.296
5	14.2488	14.4277	9.8471	15.9547	14.3354	15.7429

Table 3. SSIM

Image	NLP	RIVD	CBUE	EUIV	DCP	Proposed
1	0.6461	0.7017	0.6326	0.7487	0.7620	0.8792
2	0.7577	0.2686	0.5706	0.7635	0.5518	0.8392
3	0.6525	0.7473	0.5784	0.8268	0.8096	0.9012
4	0.7968	0.5315	0.5108	0.8136	0.7537	0.9167
5	0.7278	0.8361	0.6758	0.8636	0.8220	0.9071

Table 4. SC

Image	NLP	RIVD	CBUE	EUIV	DCP	Proposed
1	1.1503	2.6949	0.5048	0.7487	2.6949	0.9681
2	1.2296	5.7346	0.4748	0.7635	5.7346	1.1117
3	1.432	2.1327	0.4772	0.8268	2.1327	0.8243
4	1.1588	5.2824	0.4674	0.8136	5.2824	0.6433
5	1.2182	1.7248	0.1884	0.7602	1.7248	0.7320

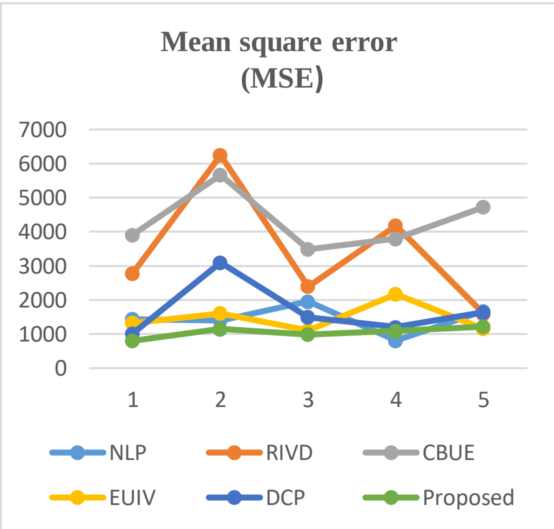

Fig. 4

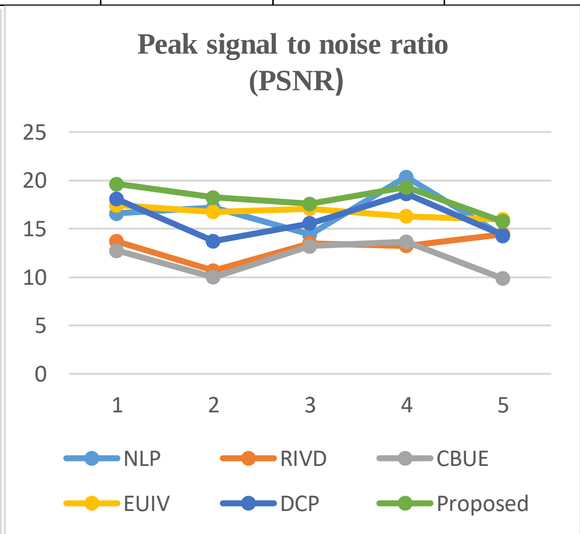

Fig. 5

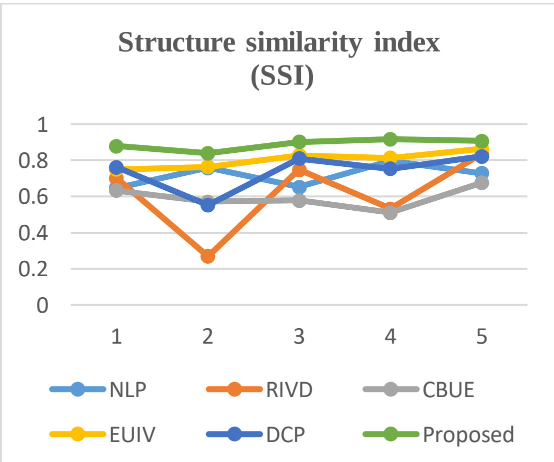

Fig. 6

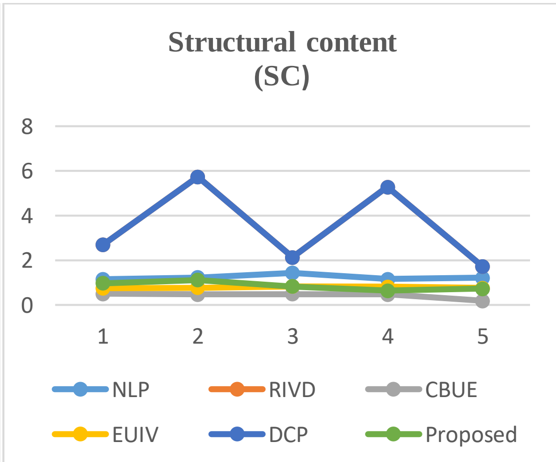

Fig. 7

IV. CONCLUSION

In this paper, we proposed a method to enhance underwater video and images. The proposed method makes use of color channels, image decomposition, and color balancing schemes to generate enhanced results. The proposed method mainly consists of four steps: color correction, YUV channel decomposition, Y channel improvement, and generation of the final image. The first step of the proposed method is to change the colors of the original image. Next, the transformed RGB picture is translated into a YUV channel, and then the luminance (Y) component is transformed to improve its efficiency. The third step makes use of average filtering and histogram equalization along with principal component analysis. . Finally, in the fourth stage, YUV color space is transformed into RGB color space. For underwater video enhancement, source videos are divided into frames, and each frame is enhanced using the suggested methodology. These frames are blended together to provide enhanced underwater videos. Based on the findings, we can say that the proposed model is significantly better in performance than the other techniques.

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