Investigating Different Filter Analyses for Underwater Image Enhancement Using Global Equalization

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Abstract. Underwater photography usually leads to significant blurriness and contrast decreases because of light absorption and scattering, This will restrict the utilization of important image data. In this research, suggest a technique,that addresses that kind of problem. This work consists of two stages, such as pixel intensity centre regionalization and global histogram equalization. The image is computed using a pixel intensity center localization approach based on various color models such as RGB, HSV, and YCbCr also uses various filters, in particular the Gaussian filter, bilateral filter, guided filter, top-hat filtering, bottom-hat filtering, top-bottom hat filtering, Top-Bottom hat filtering, Box filter, mean filter, Wiener filter. The histogram's global equalization is used to adapt the image color based on the attributes of each channel. The proposed compression strategy can provide bright images without adding over-enhancement or additional computational effort. Comparison of quality and quantity results indicates the advantages of the various filters and color modes for underwater images.

Keywords: Image color models, pixel intensity center regionalization,local equalization, global equalization.

1 Introduction

In the world, the ocean holds 96.5% of the world's water, which covers 71% of the planet's surface. humans have never explored or even seen more than 80% of the ocean surface. These hidden surfaces have many important pieces of information.Underwater image processing is one of the most significant study fields to examine the underwater environment.Now -a- day many different catagery research have utilised underwater image processing, including underwater microscopic detection, terrain mapping, mine detection, communications lines, and autonomous underwater vehicles.Image processing is one of the biggest research area to produce the image clarity via various processes like enhancement, classification, restoration, segmentation, and so on. The main phase in image processing is fillering, which produces high-quality images. The proposed study includes local and global approaches along with the analysis of several filters for local picture improvement.

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2 Methodology

Images taken underwater generally show severe colours,Light scattering and absorption cause a reduction in distortion and contrast.To address the above problems, proposed work block diagram show in fig.1 deal with many image color models such as RGB, HSV and YCbCr color models.The undewater enhancement and target detection literature processes are identified in the HSV, RGB, and YCbCr color models when compared with other color models. due to the fact that this proposed work targeted these three color models. Three channels compose the color image. Each color has its personal channel.This model three primary color components are red, green and blue. Only this proportionate ratio of these three colors may create any other color.Using conversion factors and built-in functions, the ARGB value is transformed to HSV and the YCbCr value in order to increase the recognition's accuracy.In the YCbCr color space, luminance data is saved as a single component (Y), whereas chrominance data is stored as two color-difference components (Cb and Cr). Cb denotes the difference between the blue component and the reference value. Cr represents the difference between the red component and a reference value.[**?**]

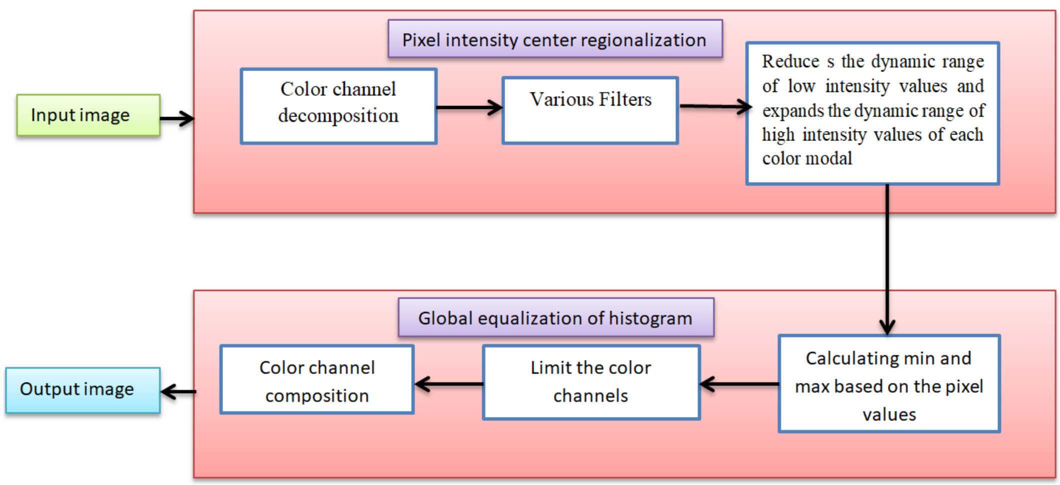

Fig. 1. Block Diagram of proposed method

3 Pixel Intensity Center Regionalization

The first stage of the proposed work deals with the various color components and different filters. The above paragraph discussed the three important color models in underwater image processing, such as RGB, HSV, and YCbCr.This color space, combined with various filtering [**?**][**?**] that is particular Gaussian filter, Bilateral Filter, Guided filter, Top-hat filtering, Bottom hat filtering, Top- Bottom hat filtering, Box filter, Mean filter, Wiener filter.

The Gaussian low-pass filter allows low-frequency impulses to pass while suppressing high-frequency frequencies. An underwater image's noise is regarded as a high-frequency signal. The normalized Gaussian function was denoted by an equation 3.

$$AB[I]_s = \sum_{t \varepsilon S} A_\sigma(\|s-t\|) I_t \tag{1}$$

Bilateral Filter, similar to Gaussian convolution, the bilateral filter is also defined as a weighted average of nearby pixels. The bilateral filter, on the other hand, takes into consideration the difference in value with the peers to preserve edges while smoothing.

$$BF[I]_s = \frac{1}{W_s} \sum_{t \in S} A_{\sigma_s}(\|s-t\|) A_{\sigma_r}\left(|I_s - I_t|\right) I_t \tag{2}$$

The normalisation factor and the range weight have been introduced into the original equation as new terms. The phrases sigma values and spatial extent of the kernel, or size of the neighbourhood, relate to the minimum amplitude of an edge and the spatial extent of the kernel, respectively. It ensures that only pixels with intensity levels comparable to the center pixel are considered for blurring while keeping sharp intensity changes. The sharper the edge, the lower the value of sigma. As an edge-preserving filter, a guided filter employs a local linear model.The filter method that is carried out per pixel and produced at each individual pixel is essentially the result of multiplying every pixel in the input image by a weight that we will create using a guiding image for that specific pixel.

$$t_i = \sum_j W_{ij}(I) s_j \tag{3}$$

The function of the guided picture I is represented by the equation above, where q is the output, p is the input, W is the weight, and i, j are the pixel indexes. The top-hat filter has the property of enhancing sharp edges by applying the opening operator. It returns the difference between the result of morphological opening operation and the original data f.

$$Top_{hat}(\mathrm{f}) = \mathrm{f} - (\mathrm{f} \quad \mathrm{Y}) \tag{4}$$

The bottom-hat filtering, also called as black-top-hat filtering, is given by,

$$Bottom_{\mathrm{at}}(\mathrm{f}) = (\mathrm{f}Y) - \mathrm{f} \tag{5}$$

Top-hat and Bottom hat filter togrther to produce the top-bottom hat filter outputs.

$$Box(a,b) = \sum_{a'=0}^{a} \sum_{b'=0}^{b} I\left(a', b'\right) \tag{6}$$

The mean of all the values in the immediate neighbourhood is used to replace the value of each pixel. If f(i,j) is a noise image, one can derive the normalised image g(x,y) by,

$$g(a,b) = (i,j) \in S1/n \sum f(i,j) \tag{7}$$

Wiener filters are most commonly used in the frequency domain. To extract X(a,b) from a degraded image x(n,m), use the Discrete Fourier Transform (DFT). The original image spectrum is approximated by multiplying X(a,b) by the Wiener filter G(a,b):

$$\hat{S}(a,b) = G(a,b)X(a,b) \tag{8}$$

The dynamic range of a picture can be lowered after filter operation by replacing the logarithm of each pixel value with its original value. As a result, low intensity pixel values are improved.

4 Global Equalization of Histogram

The second global equalization process, In this stage, the splited Red, Green and Blue, channels Hue, Saturation and Intensity, channels Luminance(Y), Chroma Blue(Cb), and Chroma Red (Cr) channels are more similar.[**?**]As a consequence, each channel color is rectified using a histogram correction global equalisation approach[**?**].The image's pixels are broadly scattered across the whole intensity level range.yang2019depth However, the intensity level of the output is limited by the global equilibrium strategy's minimum and maximum bounds.The limit technique is used to decrease the impacts of image under- and over-correction.[**?**]

$$Px(\mathrm{CH}) = a_{\min} + (P(x) - P_{\min})\left(\frac{a_{\max} - a_{\min}}{P_{\max} - P_{\min}}\right) \tag{9}$$

Where, αmin, αmax, αmin and αmax are the minimum and maximum intensity values.

5 Simulation Results

Simulation is preformed in MATLAB and the parameters given in the table 2.[**?**]

Proposed method qualitative analysis for RGB, HSV and YCbCr Model in various filters as shown in figure 3, In the figure we get different types of image clarity depends on the model and filters.In our input underwater image consist of fishes coral and some rocks but in thes thinks are hidden due to the underwater In our proposed method produced image clarity,fish sharpness,corel brightness,water colour, deapth clarities operies in the ouputimages. Thus the aperance for RGB modal Gaussian,guided,Box,mean,wiener filters produced quality outputs, In HSV model Guided,Box,mean, wiener,average filter are produced quality outputs, In YCbCr model only Guided and Top hat filter produced quality output.

In proposed method output enhanced images are analyzed quantitatively as well as qualitatively. In the quantitative analysis we analyzed the parameters Blind/Reference less Image Spatial Quality Evaluator, Entropy, Perception based Image Quality Evaluator ,Peak signal to noise ratio, mean-square error, Signal to noise ratio.Here three models RGB,HSV, YCbCr compared parameter measurements are given in figure 2.In order to achieve the enhanced output which gives RGB and HSV color models.When comparitive analyzes of above parameters correct range of results are getting in HSV color model.

Table 1: Quantitative parameter comparision

PARAMETERS		BRISQUE	ENTOPY	PIQE	PSNR	MSE	SNR
RGB Model	GaF	50.3804	5.8075	46.8305	11.3780	4.7346	12.2143
	BiF	29.8076	6.6763	9.7431	15.5126	1.8274	14.5136
	GuF	51.1851	6.5220	63.6235	12.3801	3.7589	12.1686
	T-H F	43.4543	3.9989	34.3096	9.6815	6.9973	11.3808
	B-H F	43.4002	4.0454	34.7587	8.8524	8.4692	11.3892
	T-BH F	37.9569	5.7524	33.0540	11.1193	5.0251	12.2274
	Bo F	33.8889	5.9413	52.5186	12.3813	3.7579	12.2161
	MF	33.9976	5.9454	44.3834	12.3780	3.7608	12.2208
	WF	44.3172	6.4080	60.4366	12.3650	3.7721	12.1682
HSV Model	GaF	47.0611	7.5308	45.6811	7.2669	1.2201	13.1919
	BF	37.0597	6.8564	20.3705	7.2629	1.2212	18.4754
	GuF	49.1783	7.5952	48.0341	7.2687	1.2196	12.8491
	T-H F	43.4517	6.7688	58.2809	7.2580	1.2226	12.2492
	B-H F	43.2927	6.8097	57.1493	7.2585	1.2224	12.4246
	T-BH F	29.1219	7.5403	49.5259	7.2668	1.0000	13.1628
	Bo F	37.0474	7.5961	44.7517	7.2688	1.2196	12.8561
	MF	29.7886	7.5785	36.0669	7.2688	1.2195	12.8560
	WF	43.7337	7.5940	47.1238	7.2688	1.2196	12.8443
YCbCr Model	GaF	48.5241	5.8829	44.8873	9.6664	7.0217	10.3790
	BiF	33.1824	7.0145	36.9506	12.2443	3.8784	13.3198
	GuF	46.0332	6.3913	54.8787	10.1204	6.3247	9.8995
	T-H F	40.3876	5.9521	45.8908	9.5469	7.2176	10.4880
	B-H F	32.8598	5.8153	47.1942	8.8195	8.5336	10.4863
	T-BH F	27.9653	5.9147	41.7712	9.7539	6.8816	10.4346
	BoF	47.5040	4.5666	56.7190	7.2725	1.2185	8.9321
	MF	44.2188	4.5599	52.0449	7.2725	1.2185	8.9342
	WF	52.768	4.5623	52.3397	7.2725	1.2185	8.9326

[Expansion - GaF-Gaussian filter,BiF-Bilateral Filter, GuF-Guided filter, T-H F - Top-hat filtering, B-H F - Bottom hat filtering, T-BH F - Top- Bottom hat filtering, BoF - Box filter, MF - Mean filter WF- Wiener filter, Av- Average filter]

6 Conclusion

The visibility analysis of underwater image enhancement helps to identify the tiny information identification in various application. Considering that the military images usually have the drawbacks.such as low contrast, low visibility in depth of water. Poor Visibility of these images generate

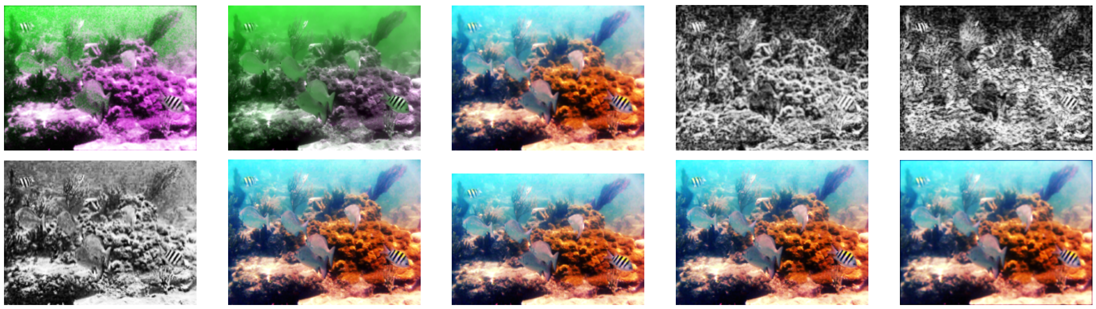

Fig. 2. RGB Model (a)GaF (b)BiF (c)GuF (d)T-H F(e)B-H F (f) T-BH F (g) BoF (h)MF (i) WF (j)Av

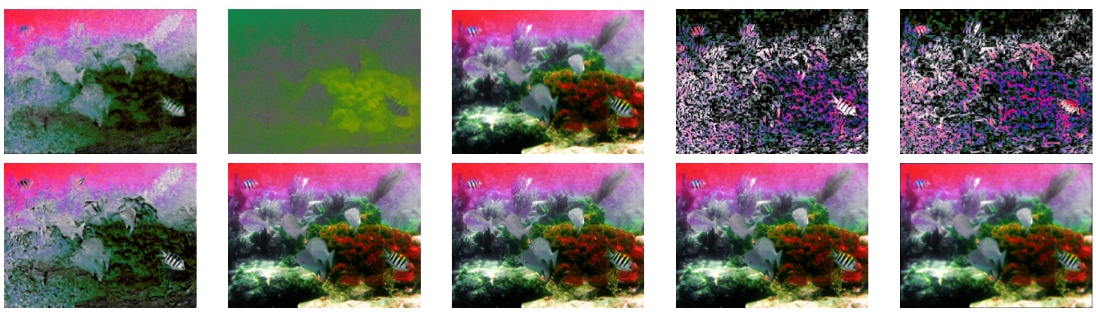

Fig. 3. HSV Model (a)GaF (b)BiF (c)GuF (d)T-H F(e)B-H F (f) T-BH F (g) BoF (h)MF (i) WF (j)Av

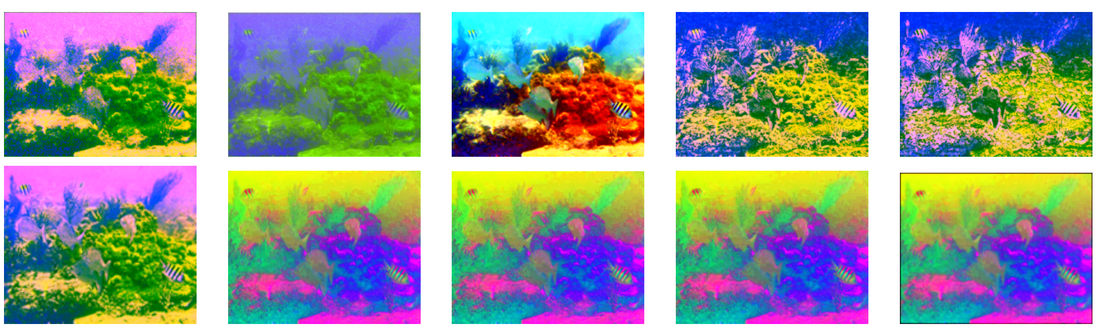

Fig. 4. YCbCr Model (a)GaF (b)BiF (c)GuF (d)T-H F(e)B-H F (f) T-BH F (g) BoF (h)MF (i) WF (j)Av

significant problem that limit the perceptual image quality and performance of the images. In this paper an underwater image visibility enhancement depends on various filters and various color models are presented our proposed algorithm significantly, enhanced the local contrast, details of the scene greatlywhile retaining the original images naturalness. e. The experimental results demonstrate that the guided filter ,Box filter, mean filter, wiener filter increases the visual quality of underwater image with RGB and HSV models are gets proved performance metrices effectively.

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