

Restoring Images inside Water by using CNN

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Abstract--Images below water always affected from quality degradation because of scattering and light absorption in water medium. There are breakthroughs in restoring images inside water, but the captured images are not in a good quality. We have to know the reasons for the reduction in quality in water image formation model (IFM). Then, we get an approach to the methods for restoring, by IFM approaches. Then we have to make a experimental model in IFM. For IFM methods include algorithms like parameter estimation.

Keywords: Image restore, Convolution Neural Networks(CNN), image formation model(IFM), optical imaging

I. Introduction

The chemical and physical aspects characteristics always affect the images below quality.

For increasing the range of imaging, we have to use artificial light sources. But, they are affected by absorption and scattering. Image enhancement makes use of the algorithms that makes an Image to have good color contrast in water. This can be a challenge because of the environment inside where images can be degraded by water turbidity, scattering, light absorption.

Fig.1. Interaction between camera and scene, light, transmission medium. The three types of light energy received by the camera are the direct transmission; forward scattering; background scattering.

II. Image Enhancement

They are used to increase the image contrast and color. It used pixel based intensity redistribution and some of the

principles of images in water are not used. Earlier, the studies of images below water enhancement concentrated on the outdoor based image enhancing methods as directly to images below water. Present methods concentrated on the characteristics of water images like low contrast, hazing, color cast.

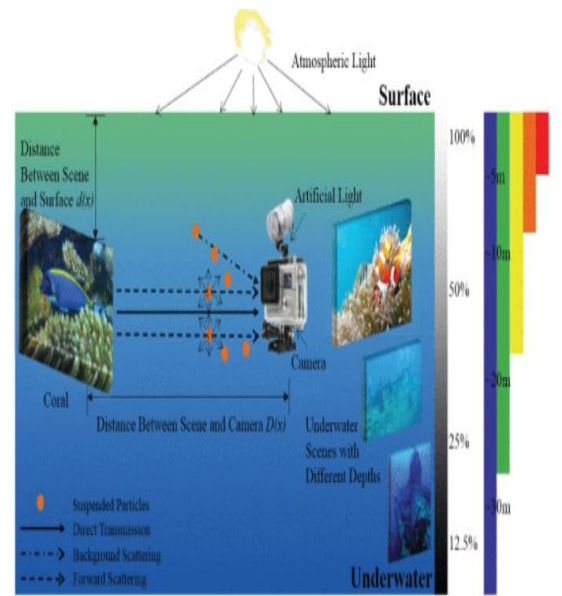


Fig.1. Diagram of optical imaging inside water

2.1. Spatial Image Enhancing

Spatial Image Enhancing refer to the image plain like direct manipulation of pixels. They are like modifying Fourier transform of an image.

A. SCM-Based Image Enhancement

Firstly, Histogram Equalization, secondly, Contrasting Adaptive Histogram Equalization, Thirdly, Gamma based Correction, and Generalized based Unsharpened used for low light images for increasing their visibility. For changing the saturation of colors we use methods like gray edge and white balance.

B. MCM-Based Image Enhancement

The correlation between the images distortion before and after. This method enhancing the image color. The data gained from scenes verifies the effectiveness and feasibility of the method. Similarly other methods like Integrated color model, Von Kries Hypothesis, Recursive Adaptive Histogram Modification showed the effectiveness and feasibility.

2.2. Transforming Image Enhancing

This method can transform the spatial imaging into frequency based. The images inside water quality can be improved by the amplifications suppressing the component like low frequenting simultaneously with the component of high-frequency. But the problem is that they amplify more for the noise and the caused color distortion.

2.3. CNN Image Enhancing

It is the Convolutional Neural Network. It basically focus on the images

III. IFM Image Restoring

It contains effective degrading model by understanding Images inside water mechanism.

3.1. Prior Image Restoring

Here we can use different prior based mechanisms like dark channel prior, images inside water light attenuate prior and others.

The following are the different priors that can be used for restoring images inside water.

A. DCP Image Restoring

DCP is for dehazing images. It is between an images inside water and a hazed outdoor image, it is applied to enhancing images inside water.

B. DCP Image Restoring

Inside water the propagation of red light is fast than blue and green lights. Its domination is in dark. Dark Channel prior is used for eliminating the influence of red light.

C. MIP Image Restoring

It contains GB and the R channels. The Attenuation between them is strong. A prior proposed known as Maximum intensity Prior. This prior is used to identify max G max B max R intensity channel.

Year	Methods	BL Estimation	TM Estimation	Prior
2010	[97]	$I^r(\arg \min MIP^r(x))$	$t^r = MIP^r(x) + (1 - \min MIP^r(x))$	MIP/MIP
2010	[17]	$I^r(\arg \max P^r(x))$	$t^r = 1 - \min_{y \in \Omega(x)} (I^r(y)B^r)$	DCP/DCP
2011	[100]	$I^r(\arg \max_{x \in \Omega(x)} \sum_c I^r(x))$	$t^r = 1 - \min_{y \in \Omega(x)} (I^r(y))$	DCP/DCP
2012	[19]	$I^r(\arg \max I^r(x))$	$t^r = 1 - \min_{y \in \Omega(x)} (I^r(y))$; $t^r = (t^r)^{\beta^r}$	DCP/DCP
2013	[101]	$I^r(\arg \min (I_{dark}^r(x) - (\max I_{dark}^r(x))))$	$t^r = 1 - \min_{y \in \Omega(x)} (I^r(y))$; $t^r = \tau \max_{y \in \Omega(x)} I^r(y)$; $\tau = \frac{\arg(\min_{y \in \Omega(x)} I^r(y))}{\arg(\max_{y \in \Omega(x)} I^r(y))}$	MIP/UDCP
2013	[95]	$I^r(\arg \max I^r(x))$	$t^r = 1 - \min_{y \in \Omega(x)} (I^r(y))$	UDCP/UDCP
2015	[98]	$I^r(\arg \max_{x \in \Omega(x)} \sum_c I^r(x))$	$t^r = 1 - \min(\min_{y \in \Omega(x)} (I^r(y)), \lambda \min_{y \in \Omega(x)} Sat^r(y), \min_{y \in \Omega(x)} (I^r(y)))$; $t^r = (t^r)^{\beta^r}$	RCP/RCP
2015	[102]	$I^r(\arg \max_{x \in \Omega(x)} I^r(x) - I^r(y))$	$t^r = 1 - \min_{y \in \Omega(x)} (I^r(y))$; $t^r = (t^r)^{\beta^r}$; $\beta^r = \frac{I^r(x) - I^r(y)}{I^r(x) - I^r(y) + \epsilon}$	DCP+MIP/DCP
2015	[103]	$\frac{1}{ \Omega(x) } \sum_{y \in \Omega(x)} I^r(x)$	$t^r = f_{\beta}(C, [R, x])$	DCP/BP
2016	[104]	$Avg(I^r(\arg \min MIP^r))$	$t^r = 1 - \min_{y \in \Omega(x)} (I^r(y))$	MIP/UDCP
2017	[105]	$\alpha \theta_{max}^r + (1 - \alpha) \theta_{min}^r$	$\theta_1 \theta_1 d_0 + (1 - \theta_1) d_1 + (1 - \theta_1) d_2$	IBLA/IBLA
2018	[99]	$I^r(\arg \max_{x \in \Omega(x)} d(x))$	$t^r = N \text{reer}^{d(x)}$; $d(x) = ULAP(x)$	ULAP/ULAP

Fig.2. BL Estimation, TM Estimation, Prior.

D. More Image Restoring Methods

Apart from the priors, some priors which are rarely used but shows good effective in water like Blurriness Prior, generalized dark channel prior, water light attenuation prior. They also work effectively, but not used.

3.2. CNN-Based Image Restoration

An algorithm called as new white balancing algorithm[1] is used for improving original images in water quality. After color correction, it uses CNN[6] to estimate BL and TM and then restoring the final images. Similarly Barbosa et al. used end-to-end-framework

CNN [6] image restoring uses feature learning forestimating BLs or depth maps. Its performance is based on on training data and the network architecture design.

IV. Improving quality Methods for images inside water: Experiment Comparison

The following are the experimental comparisons for quality improvement in water images.

4.1. The Methods to be Comprised

They contain methods like HE, CLAHE, distribution and relative global histogram stretching.

4.2. Image Evaluation Metrics

The quality of the image is affected by imaging conditions, the optical performance of equipping image, Processing an image, instrument noise. IQA[1] is to divide into two types. They are (i) subject quality assessment (SQA)[1], (ii) object quauty assessment (OQA)[1].

SQA[1] based human visualizing systemfor gaining subject impression of the images. We have to repeat experiments for generating a dataset. Then human observations are done. But It contains low efficiency.

OQA[1] contains the mathematical model for calculate a quality index. The efficiency of this model is better than SQA[1]. OQA[1] methods are non-referencing, reducing referencing, full referencing.

4.3. Assessing Optical Parameters

A. Comparing BL Estimating Model:This estimating determines the visual effectand color tone of restored images. The algorithms of TN depend on the results of BL[2]. It is essential to carry out different BL estimation models. Select four typical images, the foreground containing the swimming batfish,cliffs, wrecked shipsin low watershallow-sea fishes under natural lightsource.

From Fig. 4, the accuracy of the channels is less than 80%.

B. Comparing TM Estimating Model:

Contains estimation through subjective assessment because of transmission map. If the object is closer them the TM[3] value is more and it shows more white. If the object is far then more dark it shows. This shows the performance.

Four water images are taken and comparisons of accuracy by TM[3] estimation.

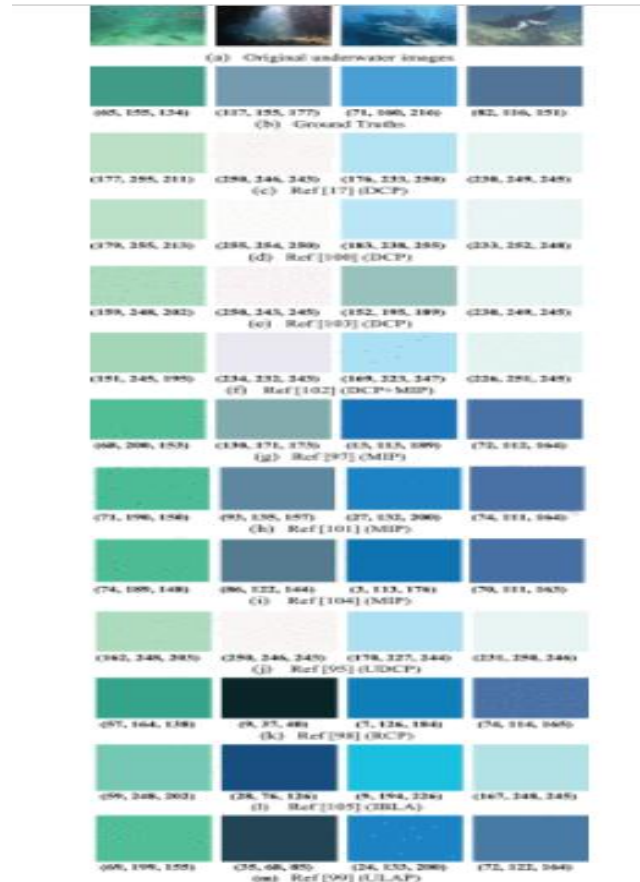


Fig 3. ComparingBL estimating methods

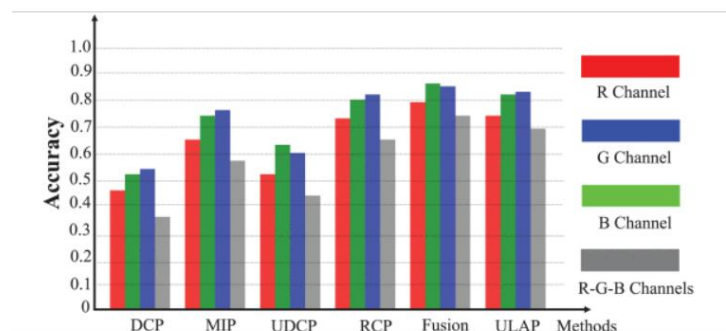


Fig 4.Comparingaccuracy.

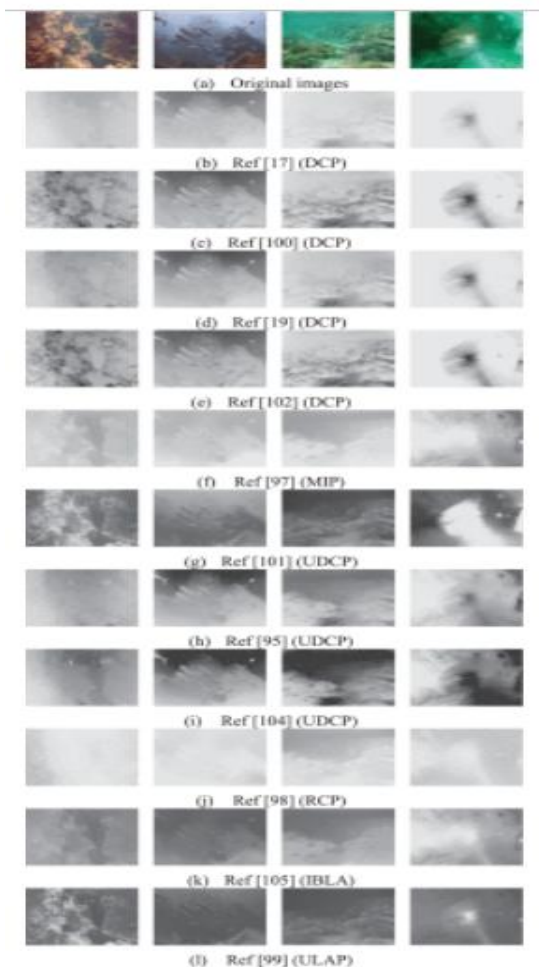


Fig 5. Comparing accuracy of TM estimating.

Fig.5.shows wrong TM[3] for first three but correct for the last one. It is because of maximum R channel and GB is evaluated by UDCP.

V.Total Performance of enhancing images inside water and restoring images.

Here check for the total performance of underground image.

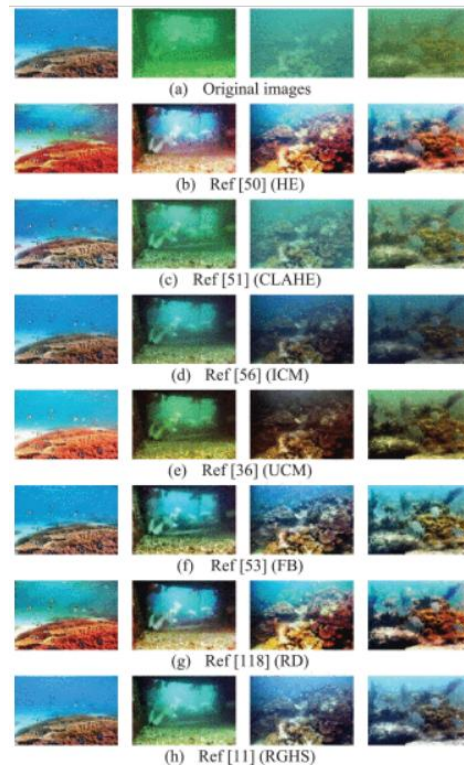


Fig 6. Comparing results of IFM enhancing images in water

It contains two analysis. They are: Subjective analysis and Objective analysis.

A. Subject Analyzing

HE [4]methods handle red tone. They can even amplify original image noises. Here CLAHE[4] and RGHS[4] reduce the sharpness of blind pixels.

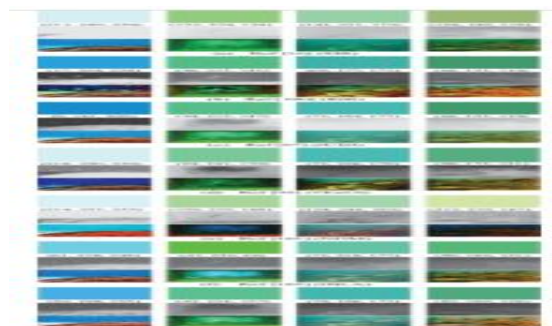


Fig 7. Comparing BL[4]s, TM[3]s, restoring images of IFM image restoring.

As shown in Fig.7, IBLA, ULAP producing good restoring images.

B. Objective Analysis

Image restorations are used to increase the quality of images inside water.

Table shows the images that are enhanced and restored. So the algorithms for increasing the quality work for restoring the images.

TABLE 1: Analysis of Restoring and Enhancing Results

Compared methods	Image Quality Assessment Metrics					
	ENTROPY	BRISQUE	NIQE	UIQM	UCIOE	
IFM-free underwater image enhancement	HE	7.8139	28.6079	3.9654	4.0399	0.6818
	CLAHE	7.1132	27.3445	3.6338	2.0644	0.6567
	ICM	6.9117	33.1758	3.4253	2.2999	0.5872
	UCM	7.2643	28.2424	3.6339	3.3228	0.6131
	FB	7.5269	32.9730	3.9176	2.7567	0.6684
	RD	7.7487	29.0286	3.7631	3.2654	0.6721
RGHS	7.4759	28.3178	3.5161	2.0116	0.6176	
Avg(Var)	7.04(0.09)	29.67(4.86)	3.69(0.03)	2.82(0.49)	0.64(0.001)	
IFM-based underwater image restoration	SIR	6.3973	33.5067	3.3175	0.1605	0.5054
	IUID	6.5484	29.6948	3.3645	0.7895	0.5270
	RIR	6.4863	27.5484	4.2616	2.5178	0.5578
	NOM	7.3464	33.2872	4.3518	4.1640	0.5937
	TEoLI	6.9915	23.7730	3.4819	2.8488	0.5820
	IBLA	6.8470	31.4013	3.5331	1.4764	0.5918
ULAP	6.7583	29.5713	3.4304	3.7060	0.5872	
Avg(Var)	6.77(0.09)	29.82(9.99)	3.68(0.16)	2.24(1.9)	0.56(0.001)	

VI. Conclusion

Increasing quality methods of single image inside water can help researches to understand the knowledge of images in water. We summarize the quality improvement images into the following categories: (i) IFM[5] free image inside water enhancing (ii) IFM[5]-based image inside water restoring. We then provide an experimental-based approach. These overall methods makes understand the knowledge of image in water.

References

1. R. C. Gonzales, R. E. Woods, Digital Image Processing 2nd Edition. New Jersey: Prentice-Hall Inc., 2002.
2. S. Hashemi, S. Kiani, N. Noorzi, M. E. Moghaddam, "An image enhancement method based on genetic algorithm," in Proc. of 2009 IEEE International Conference on Digital Image Processing, March 2009, pp. 167–171.
3. .C. Munteanu, A. Rosa, "Towards automatic image enhancement using genetic algorithms," in Proc. of 2000 IEEE Congress on Evolutionary Computation, vol. 2, 2000, pp. 1535–1542.
4. Y. W. Chen, Z. Nakao, K. Arakaki, "Genetic algorithms applied to neutron penumbral imaging," in Optical Review Journal, vol. 4, no. 1B, 1997, pp. 209–215.
5. Y. W. Chen, Z. Nakao, X. Fang, "A parallel genetic algorithm based on the island model for image restoration," in Proc. of 1996 IEEE Signal Processing Society Workshop, 1996, pp. 109–118.
6. F. Saitoh, "Image contrast enhancement using genetic algorithm," in Proc. of IEEE International Conference on Systems, Man, and Cybernetics, vol. 4, 1999, pp. 899–904.