Underwater Image Enhancement Using Convolution Neural Network

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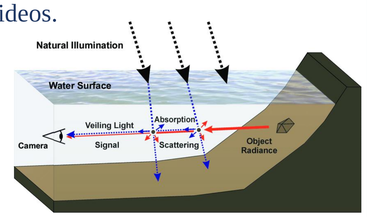
Introduction

Due to the demand of underwater imaging applications such as underwater archaeology and species identification is important to have good quality underwater images/videos.



Because of that,

- Underwater environment has become poorly visible, low contrast, with blurry or green, dark, gloomy environment.
- Difficult to restore and enhance the degraded underwater image using traditional image enhancement techniques.

Background

There are several techniques including histogram equalization, white balancing, and fusion-based methods to enhance digital images. But underwater image enhancement is more advanced due to introducing new constraints like light absorption, low contrast, noise, and poor visibilities, as well as the inherent structure of the ocean, etc. The introduction of convolutional neural network (CNN) shows better performances in various applications of computer vision due to its ability to extract important features in a more reliable way.

Objective

To design a CNN architecture with the help of reliable hyper parameter tuning techniques to carry out better performance in underwater image enhancement.

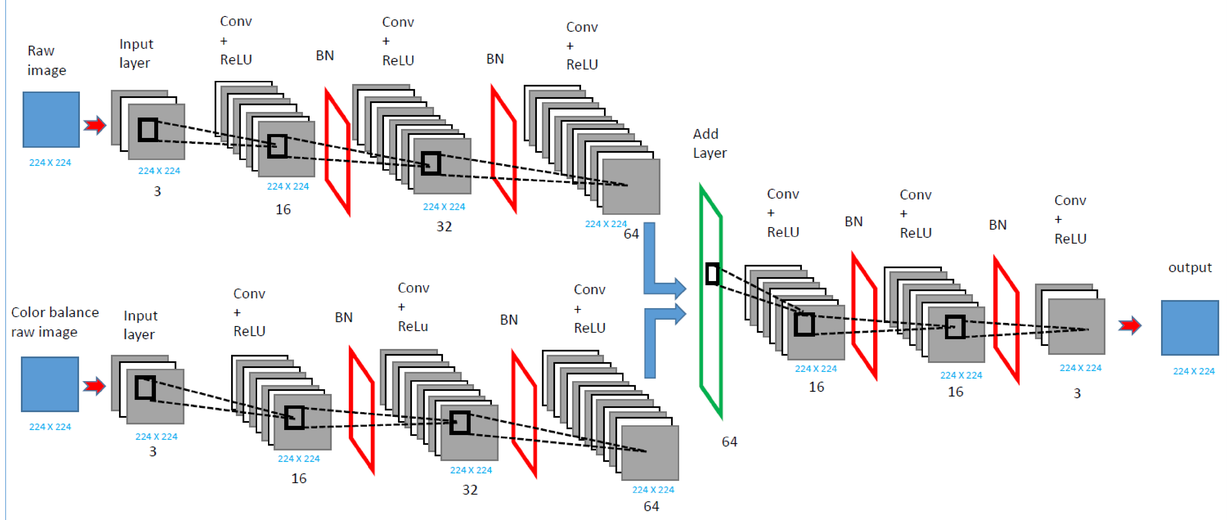
Dataset

We used the Underwater Image Enhancement Benchmark (UIEB) dataset to train the proposed model. We resized all images into 224×224 resolution.

Raws:	890 real-world images
References:	890 images correspond to the raw images
Challenging:	60 images cannot obtain satisfactory reference images

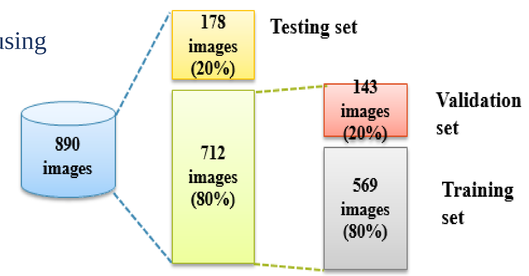
Model Architecture

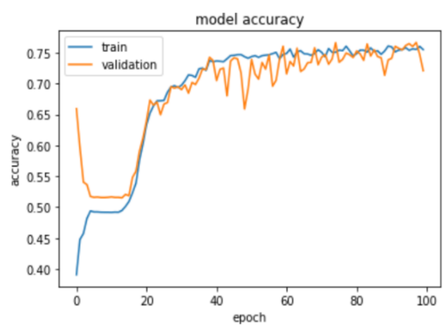
- Initially, we produce colour-balanced images for each and every raw image in the dataset.
- After that, we feed the raw images and the corresponding colour-balanced images into the same network and merge output feature maps to create a more accurate feature map by getting the advantages of the colour balancing technique.
- The two branch network combine and then features are learn through a single feature network.
- The output enhanced image is produced by obtain the raw image and colour-balanced image.

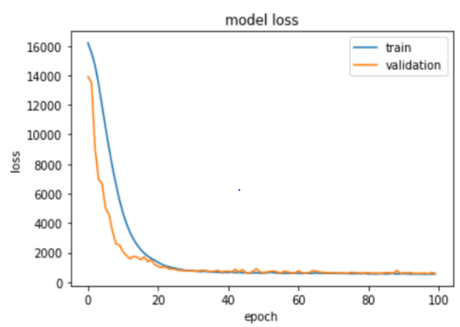


Experimental Setup

- **Model Constructions**: Keras open source library using Tensorflow backend
- **Optimization Algorithm**: Adam
- **Learning rate**: 0.001
- **Batch size**: 16
- **Loss function**: MSE







Results

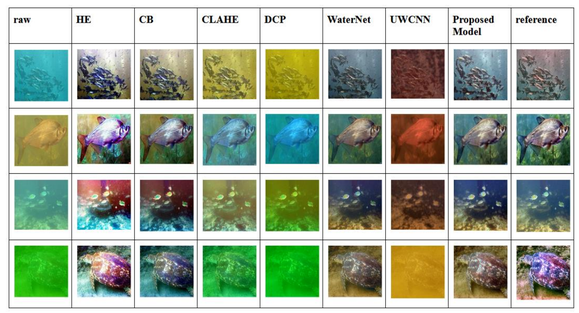
To illustrate the advantages of the proposed model, we compared it with several image enhancement methods, and image colour restoration. The proposed model achieves better performance in terms of full-reference image quality assessment.

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2$$

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Method	MSE	PSNR(dB)	SSIM
HE	3951.76	12.97	0.67
CB	4027.96	13.40	0.72
CLAHE[3]	3921.47	13.29	0.71
DCP[4]	6405.97	10.58	0.57
WaterNet[1]	1097.79	18.72	0.85
UWCNN[2]	4288.32	12.35	0.53
Proposed Model	623.23	21.55	0.86



Conclusion and Discussion

In this work, a CNN-based solution for underwater image enhancement is proposed and compared with other state-of-the-art methods. Experiments are performed on real-world underwater images, which indicates the robust and effective performance of our method. The proposed model is quantitatively evaluated using MSE, PSNR, and SSIM metrics

References

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