# Colour Correction and Enhancement Using Hybrid Learning Model for Underwater Images

B. Esther Rani[1], Dr. S. Chandra Mohan Reddy[2]
[1]*M. Tech Scholar, DECS,ECE Department, JNTUA College of Engineering(AUTONOMOUS) Anantapuramu, Andhra Pradesh, India*
[2]*M. Tech., Associate Professor, ECE Department, JNTUA College of Engineering (AUTONOMOUS) Anantapuramu, Andhra Pradesh, India*

***Abstract* - Underwater Images play major role in ocean exploration and resource engineering. Enhancement and Color Correction of underwater images is challenging because underwater Images suffer from colour castes and look bluish due to attenuation, absorption and scattering of light. In the procedure of enhancing, the texture and structural preservation is more important. In this paper, the novel deep learning algorithm along with gamma correction is proposed. In our work, the image enhancement is done by using the Convolutional Neural Network (CNN). Our process involves two stages mainly the training and testing stage. During training process, the dataset (UIEB) is collected and their up sampled and residual images are stored as a mat file. Up sampled images are computed by applying Bicubic interpolation to low resolution image and 'Y'component in Ycbcr image is considered as residual image. Convolutional neural network is created and trained using the data stored in mat files. After the training process, the test image is given as input to network designed earlier to obtain the high-resolution image. The proposed method reduces the loss of textural and structural information when compared to state of art methods.**

***Index Terms*- Underwater Image enhancement, Colour correction, Convolutional Neural Networks (CNN), Bicubic interpolation.**

## 1. INTRODUCTION

Underwater imaging is becoming more and more relevant as companies search for the abundant mineral and biological resources in oceans, rivers and lakes. Significant progress has been made in underwater exploration, but underwater image and video processing techniques still have much potential for development for computer vision applications [1].Several methods has been proposed in recent years for enhancing underwater image such as single scale retinex, multiscale retinex, Multiscale Retinex with color restoration, and path selection based method (McCann Retinex) [2]. Wavelength compensation and image dehazing algorithm is used to remove distortions caused by light scattering and color change. Energy compensation for each channel is carried out subsequently to adjust bluish tone to natural color [3]. Single image haze removal using dark channel prior is implemented to obtain high quality haze free image and produce a good depth map [4]. A Retinex based approach for single underwater image is used to enhance reflectance as well as illuminance [5]. A new variation model based on retinex is established from the conventional model without using logarithmic transformation to decompose illumination and reflectance [6] Residual learning-based framework aims to build a deeper network and improve the performance for underwater image enhancement, the Underwater Resnet is proposed according to the idea of residual learning [7]. To advance the development of image enhancement constructed a large-scale real world Underwater Image Enhancement benchmark dataset and also underwater image enhancement network called water net which shed light on future research in underwater image enhancement [8]. Huang et al. [9] proposed a simple strategy for shallow water image enhancement by adaptively obtaining the parameters. Li et al. [10] proposed a corrected colour distortion by defining a transfer function and using a generative adversarial network to accomplish optimization. Lu et al. proposed two methods based on deep learning model [11] these two methods achieved a good result but their application is restricted more or less by lack of training data.

Changli li [12] proposed a Retinex based algorithm to estimate the illuminance component by designing clockwise and counterclockwise paths from four diagonal of a square and also presented a linear piecewise histogram transform algorithm to improve the visual quality of the underwater images. This method fails to achieve good results when the image has high scattering effect.

In this paper, we propose a hybrid learning model which enhances the underwater image by using convolutional neural network (CNN). Underwater Image Enhancement Benchmark Dataset (UIEB) is used to train the network. The images are resized to train the network by using Bicubic interpolation method. In training process the images are stored as the mat files to train the network, after draining the network testing is done by giving the input image to the network to produce the enhanced and color corrected image which is high resolution image.

## 2. PROPOSED APPROACH

Considering the characteristics of underwater imaging and limitations of directly processing underwater images, we proposed a colour correction and enhancement of underwater images using hybrid learning model.

Our method is focused on the following steps:

1. Convert Image into low resolution and Bicubic interpolation is applied to the low-resolution image;
2. Up sampled image is transformed from RGB space into Ycbcr space;
3. Y component is processed using super resolution network;
4. Difference image is calculated from processed y component and up sampled y component;
5. Finally, add the difference image and reference image.

### A. CONVERT IMAGE INTO LOW RESOLUTION AND APPLY BICUBIC INTERPOLATION

Image taken as the input is of the large resolution which requires a lot of memory to train the network. So, it has to be reduced to low resolution this can be done by using Bicubic interpolation by considering scale factor. The low resolution image is up sampled by using Bicubic interpolation and this can also helpful to maintain same resolution as the output.

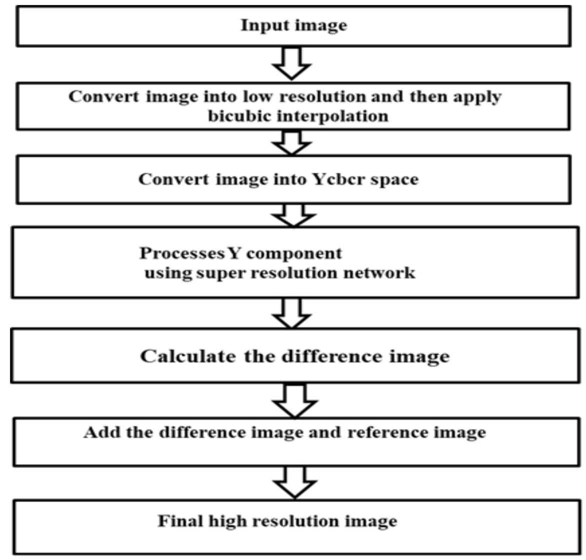



Fig 1: Flowchart of proposed method

### B. CONVERSION OF UPSAMPLED IMAGE INTO YCBCR SPACE

Ycbcr represent colour as brightness and two colour difference signals.

Y is the brightness (luma),

Cb is blue minus luma (B-Y) and

Cr is red minus luma (R-Y).

This colour space is often used in order to take the advantage of the low-resolution capability of human visual system.

Fig 2 represents the conversion of image from RGB to Ycbcr space.

Formula to convert RGB image into Ycbcr space is as follows:

$Y = 16 + 65.738*R/256 + 129.057*G/256 + 25.064*B/256$

$Cb = 128 - 37.945*R/256 - 74.494*G/256 + 112.439*B/256$

$Cr = 128 + 112.439*R/256 - 94.154*G/256 - 18.285*B/256$

### C. PROCESS Y COMPONENT USING SUPER RESOLUTION NETWORK

Y component which represent the intensities of the image is processed by using super resolution network Convolutional neural network layers are created with the network depth 10.

- First Layer is constructed as Input Layer
- Middle layers is constructed as non linear mapping layers (2 to 9)
- Final layer is constructed as output layer (Reconstruction Layer).

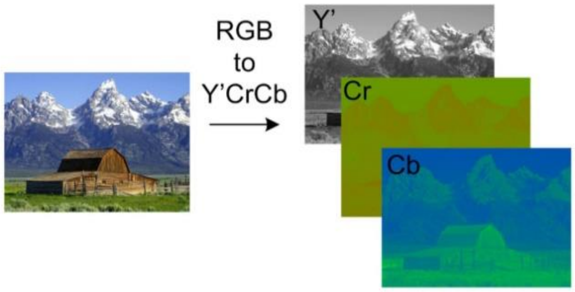



Fig 2: Conversion of image to Ycbcr

The SRCNN method can be divided into three parts: Patch extraction and representation, non-linear mapping, and reconstruction. Patch extraction and representation refers to the first layer, which extracts patches from the low-resolution input image.

The operation of the first layer is as follows:

$F1(Y) = max(0, W1 * Y + B1)$

Where, F1 represent the mapping function,

Y represents the Bicubic interpolated low-resolution image,

W1 represent the filter weights, and

B1 represent the biases

Non-linear mapping refers to the middle layer, which maps the feature vectors linearly to another set of feature vectors i.e., the high-resolution features.

The operation of the middle layer is as follows:

$F2(Y) = max(0, W2 * F1(Y) + B2)$

Reconstruction aggregates these high-resolution features to generate the final high-resolution image.

The operation of the last layer is as follows:

$F(Y) = W3 * F2(Y) + B3$

Layers in the network:

- Convolution layer
- Relu layer
- Batch normalization layer

A convolution layer transforms the input image in order to extract features from it. It is also known as a convolution matrix or convolution mask. This kernel slides across the height and width of the image input and dot product of the kernel and the image are computed at every spatial position.

The ReLU layer applies the function

$f(x) = max(0, x)$

to all the values in the input volume. This layer just changes all the negative activations to 0. This layer increases the nonlinear properties of the model and the overall network without affecting the receptive fields of the convolution layer.

Batch normalization is a technique for training very deep neural networks that standardizes the inputs to a layer for each mini-batch.

This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks.

After creating the network, it is trained using the images taken from UIEB dataset. Images are converted into mat files to train the network .The weights are updated using back propagation algorithm. Back propagation uses chain rule.

The weights can be approximated by following equation

$W_{(n+1)}=W(n)+\eta[d(n)-Y(n)]X(n)$

Where:

n: Training step (0, 1, 2 …).

W (n): Parameters in current training step.

Wn = [ bn, W1 (n),W2(n),W3(n),…, Wm(n)]

η: Learning rate with a value between 0.0 and 1.0.

d (n): Desired output.

Y (n): Predicted output.

X (n): Current input at which the network made false prediction

D. CALCULATE THE DIFFERENCE IMAGE AND PRODUCE OUTPUT

The processed y component from the network and Bicubic interpolated y component is subtracted to get the difference image

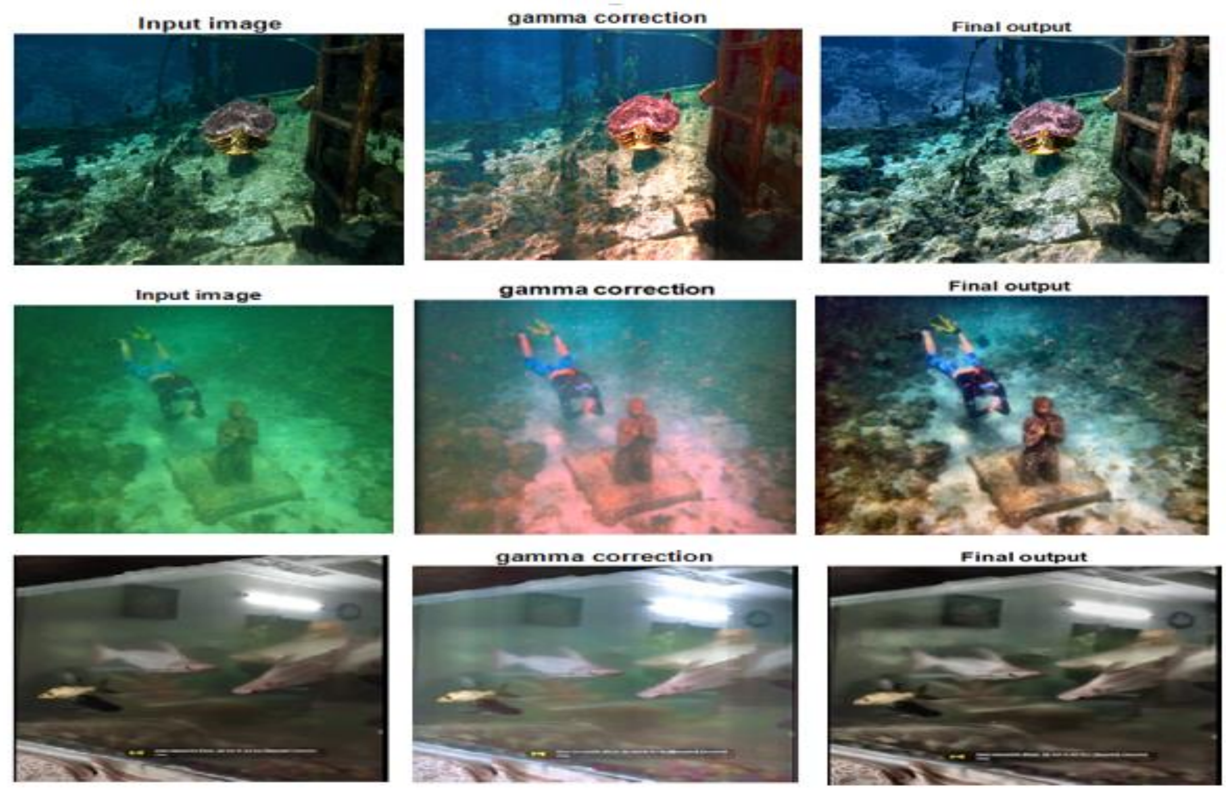
Diff image= $(ycomp)_{network} - (ycomp)_{Bicubic}$

The difference image is added to Bicubic interpolated image to get final output.

Output =up sampled image + Diff image

## 3. RESULTS AND DISCUSSION

The effectiveness of the proposed method is verified by taking large number of underwater images from dataset [8] and compared with the existing method. To evaluate the proposed method, the performance metrics such as (PSNR) Peak signal to Noise ratio, (MSE) Mean Square Error, Entropy, (NIQE) Natural Image Quality Evaluator [11], UCIQE and UIQM (Underwater Image Quality Measure) are considered. Proposed work is tested with randomly selected 100 images from the dataset (UIEB) and its average performance is calculated.




(a) (b) (c)

Fig: (a) Raw underwater image, (b) Existing method output (c) Proposed method output

Table: Average performance of 100 Images:

| | PSNR | MSE | Entropy | NIQE | UCIQE | UIQM |
|---|---|---|---|---|---|---|
| Existing | 53.21 | 3.82 | 7.73 | 3.57 | 0.48 | 4.39 |
| Proposed | 95.26 | 0.02 | 7.79 | 3.41 | 0.45 | 4.98 |

## 4. CONCLUSION

Underwater image colour correction method and an underwater image enhancement method are implemented in this research. The proposed method uses deep neural network trained by using UIEB data set and tested for several underwater images. The images processed by this method have clearer details, uniform visual effect and better color correction results comparing with the existing methods and has good performance metrics.

## REFERENCES:

[1] X.Fu, z.fan, M. ling, y. haung, x.Ding, “Two step approach for single underwater Image enhancement”, International symposium on Intelligent Signal Processing and Communication Systems, November 2017.

[2] Anil Singh Parihar, Kaviner Singh, “A study on Retinex Based method for Image Enhancement”, in second international conference on Inventive systems and control.,ICISC-2018.

[3] John Y. Chiang and Ying-Ching Chen, “Underwater Image Enhancement by Wavelength Compensation and Dehazing” in IEEE TRANSACTIONS ON IMAGE PROCESSING.VOL.21.NO.4, APRIL 2012.

[4] K. He, J. Sun, and X. Tang, ``Single image haze removal using dark channel prior," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 12,pp. 2341_2353, Dec. 2011.

[5] X. Fu, P. Zhuang, Y. Huang, Y. Liao, X.-P. Zhang, and X. Ding, ``A retinex based enhancing approach for single underwater image," in Proc. Conf. Image Process., Oct. 2014, pp. 4572_4576.

[6] X. Fu, Ye Sun, MinghuiLiWang, Y. Huang, X.Zhang and X. Ding, "A novel Retinex based approach for Image Enhancement with illumination adjustment", IEEE International Conference on Acoustic, Speech and Signal Processing(ICASSP).

[7] Peng Liu, G. Wang, Hao Qi, C. Zhang, "Underwater Image Enhancement with Deep Residual Framework", IEEE Special Section on Advanced Optical Imaging for Extreme environments, July 31, 2019.

[8] C. Li, C. Guo, W. Ren, R. Cong, J. Hou, S. Kwong, and D. Tao, ``An underwater image enhancement benchmark dataset and beyond," IEEE Trans. Image Process., vol. 29, pp. 4376_4389, Nov. 2020.

[9] ChnaliLi,S. Tang, Hon K. Kwan, J. Yan,T.Zhou, "Color Correction based on CFA and Enhancement based on Retinex with dense pixel for underwater Images", IEEE Access,2020.

[10] A. Mittal, R. Soundararajan, and A. C. Bovik, ``Making a `completelyblind' image quality analyzer," IEEE Signal Process. Lett., vol. 20, no. 3,pp. 209_212, Mar. 2013.

[11] K. Panetta, C. Gao, and S. Agaian, ``Human-visual-system-inspired underwater image quality measures," IEEE J. Ocean. Eng., vol. 41, no. 3,pp. 541_551, Jul. 2016.

[12] C. Cheng, C. Sung, H. Chang, "Underwater image restoration by red dark channel prior and point spread function deconvolution," in Proc. 2015 IEEE Int. Conf. Signal and Image Process. Appl., Oct. 2015, pp. 1-6.

[13] J. Raihan A, P. E. Abas, and L. C. De Silva, ``Review of underwater image restoration algorithms," IET Image Process. vol. 13, no. 10,pp. 15871596, Aug. 2019.

[14] A.S.A.Ghani and N. A. M. Isa, ``Enhancement of low quality underwater image through integrated global and local contrast correction," Appl. SOF Comput., vol. 37, pp. 332344, Dec2015.

[15] Y. Wang, W. Song, G. Fortino, L.-Z. Qi, W. Zhang, and A. Liotta,``An experimental-based review of image enhancement and image restoration methods for underwater imaging," IEEE Access, vol.7, pp. 140233140251,2019.