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Deep Learning Approach for Submerged Image Enhancement

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Abstract: Because of underwater pictures application in ocean engineering, ocean research, marine biology, and marine archaeology to name a few, underwater picture enhancement was widely publicized in the last several years. Underwater photos frequently upshot in low contrast, blurred, color distortion, hazy, poor visible images. This is because of light attenuation, absorption, scattering (forward scattering and backward scattering), turbidity, floating particles. As a result, effective underwater picture solution must be developedin order to improve visibility, contrast, and color qualities for greater visual quality and optical attractiveness. Many underwater picture enhancing approaches have been proposed to overcome these challenges; however they all failed to produce accurate results. Hence for this we first undertook a large scale underwater image dataset which is trained by convolution neural network (CNN) and then we have studied and implemented a deep learning approach called very deep super resolution (VDSR) model for improving the color, contrast, and brightness of underwater photos by using different algorithms such as white balance, histogram equalization, and gamma correction respectively. Moreover, our method is compared with the existing method which reveals that our method surpassesthe existing methods
Keywords: CNN, gamma correction, histogram equalization, underwater image enhancement, VDSR, white balance.

I. INRODUCTION

Enhancing submersed images is considered as a crucial task due to complicated submersed environment and lightening condition. In both image processing and underwater vision enhancing submersed images has drawn much attention in the recent couple of years. Enhancing underwater image is very important for both ocean logistics and oceanography where both freestanding and remotely controlled vehicles are extensively used for exploring marine environments. Underwater images are depicted by their deficient visibility and this is for the reason that light gets attenuated rampantly when it proceeds in water. The larger wavelengths are affected more when compared to shorter wavelengths which results in greenish blue underwater images as they lack certain wavelength components, poorly contrasted and hazy underwater images. The main factors for degradation of underwater image are absorption (which gets rid of light energy) and scattering (which alters the route of light path) which includes both forward scattering (which gives rise to blurring of image characteristics) and backward scattering (which limits the contrast of images). The effect of scattering can be increase due to marine snow which introduces noise. Due to these negative impacts, visibility is reduced, contrast is reduced, and color casts are introduced which restrict the realistic utilizations of underwater pictures and videos in the study of biology of marine life, organisms in the sea, archaeology, marine biodiversity, aquatic robot inspection to name a few. In consequence it is required to establish effectual solutions for submersed images in order to upgrade the clarity, contrast, color properties for greater visual aspect and optical appeal. In order to work out this difficulty, formerly methods depend on numerous submersed images or polarization filters, while latter methods trade in with this issue by using only details from a sole image. Regardless of the good effort, both the complete learning and perceptive scanning of many underwater image enhancement methods remain displeasing because of shortage of openly accessible underwater image dataset. To work out this difficulty we undertook a large scale submersed image dataset which is used for training the convolution neural network (CNN). Also we studied and implemented a deep learning approach called very deep super resolution (VDSR) model for underwater picture improvement in terms of color righting, Contrast adjustment and brightness by using white balance, histogram equivalence, and gamma adjustment methods respectively.

II. RELATED WORK

Underwater images are degraded by many factors such as absorption, scattering (both forward and backward scattering) which requires modeling and estimating of these factors for enhancing underwater degraded images. A diversity of proposals has been put forward for enhancing underwater images. A detailed review of these approaches is shown in this section.

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In [1], beyond 120 researches of newest development in submerged image enhancement and restoration methods counting datasets, method of working, accessible codes, and evaluation measures is summarized. For comprehensive understanding of underwater picture enhancement and re-establishment method, they examine the contribution and limitation of existing methods. Further a complete objective evaluation and study of representative techniques on five varieties of submerged scenarios is provided. In [2], proposes a Rayleigh stretched contrast limited adaptive histogram definition approach that incorporates both global and local contrast adjustment. The paper's principal purpose is to expand image particulars and boost the range of vision of underwater images while improving image contrast. [3] proposes Generative adversarial network (GAN) for generating realistic underwater pictures using in-air imagery and depth pairs in an unsupervised pipeline is used to correct color in monocular underwater photos. The pipeline is validated using real-world data. To make the initial development of the approaches easier, the waterGAN and color righting networks are trained individually. In [4], on multi-scale dense GAN, it's also suggested to improve quality of underwater images. The residual dense multiscale block is shown in the generator where multiscale, densely concatenation and residue learning enhance performance, offer more details and utilize prior details, respectively. Multiscale dense concatenation. Computationally light spectral normalization is used by discriminator to keep its training stable. In [5], a two step strategy for sole underwater picture enhancement is put forward, concentrating on two crucial issues of underwater images i.e. shift in color and low contrast. A color rectifying policy build on linear transformation is established for rectifying hue distortion and a brand-new concept for determining the best contrast technique is cast-off for trading in with contrast. In [6], proposes enhancing underwater photos in a methodical way that comprises of underwater dehazing algorithm for bringing back the sightlines, color and natural aspect of the image, as well as enhancement algorithm build on histogram distribution prior for increasing the underwater image contrast and brightness. In [7], image blurriness and absorption are used as basis for measuring underwater depth, as it is engaged in image formation model (IFM) for enhancing and repairing underwater images. Earlier IFM picture restoration procedures build on dark channel prior or the highest intensity prior to determine depth. This technique gives rise to bad restoration outcome because of lightning conditions in underwater images. In [8], a cross-breed procedure is proposed which involves color modification and underwater image dehazing. To get rid of color casts of underwater images a systematic color modification algorithm is used and an underwater image dehazing method which involves overall background light estimation algorithm is put in to refine the range of vision of underwater images. To rectify color distortion, [9] proposes a weekly supervised color shift method that does not need pair of underwater pictures for teaching and permit for underwater pictures collected in unrevealed places. Along with adversarial, cycle, and SSIM losses, they intend multi-term loss function as well, which permits the corrected result to have the same content and structure as input, however with color of an picture taken in absence of water. In [10], they studied the current intelligence algorithms such as techniques for in-depth learning in submerged picture dehazing as well as re-establishment and reveal the performance of underwater picture dehazing and color re-establishment using various ways. A color evaluation measure for underwater pictures is also introduced, as well as an overview of the principal applications of underwater images.

III. METHODOLOGY

Our work deals with enhancing underwater images by making use of an efficient deep learning method namely powerful supervised learning method. In supervised learning, the convolution neural network (CNN) is trained using labeled dataset. This network learns about each type of data.

Once the training is completed a very deep super resolution (VDSR) model is studied and implemented on test data for righting underwater images with regard to color, contrast and brightness by putting in different algorithms such as white balance (WB), histogram equalization (HE), and gamma correction (GC) respectively.

A. Convolution Neural Network

The filters are used on the pixels of any image by CNN to acquire knowledge of complete patterns.

1) *Convolutional Layer:* Numerous filters are put in to the feature map at convolution layer. After convolution, a relay activation function is cast-off for inclusion of non-linearity to the network.
2) *Pooling Layer:* After convention, the upcoming step is to do down sampling for the maximum facility. The purpose is to bring down the mobility of the feature map to put a stop to over fitting and boost the calculating speed. Max pooling is a classical procedure, which breaks feature maps into subfields and only grasp maximum values.
3) *Fully Connected Layers:* All neurons from the preceding layers are analogous to the other succeeding layers. The CNN has allocated the label as reported by the features from convolutional layers and lowered with any pooling layer.

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B. Very Deep Super Resolution (VDSR)

The difficulties faced by underwater photo enhancement techniques are identical to that of super resolution reconstruction techniques. Underwater images are degraded due to absorption, scattering which result in blurry underwater images, and details of underwater images are lost. Therefore underwater image enhancement needs color difference correction and features re-establishment. Likely, the objective of super resolution reconstruction is to re-establish image features. Figure 3.1 VDSR network architecture is shown. There are 20 convolution layers in the VDSR model. Every convolution layer employs 3×3 dimension filter, by stride of 1 as well as0-padding by1 pixel. These parameters make sure resolution of input image and output image is same. Except for the first and last layer each convolution layer includes 64 channels. First layer takes 3-channel picture information as input, converts it into 64-channel feature map, and sends it to network's main body. Reconstruction layer is the final layer. Final layer takes 64-channel feature map as input and gives 3-channel residue pictures. To create the final restored photos, the residual images are combined with the input pictures.

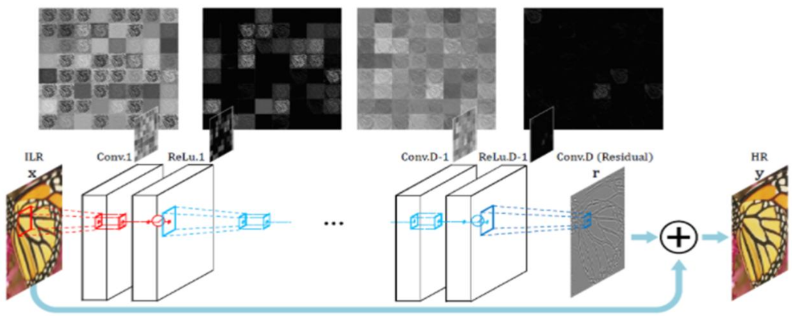

Figure 3.1: Network Architecture of VDSR

It's also possible to use VDSR model to super-resolution reconstruction, which creates high-resolution picture from low-resolution one via bicubic interpolation. As a result, while using VDSR model for restoring underwater photographs, neither the picture size for input output nor the network structure need to be changed. The network requires only appropriate and efficient training data.

IV. MODEL DESIGN

Image folder consists of thousands of underwater images for training the module.For training the module we used the neural network concept i.e. Convolution neural network. The system first uses the real time images to train the module, which consist of images of the best quality images of the underwater scenario.Next when the image is uploaded to VDSR model for restoring image quality, it undergoes three tasks such as white balance (WB), histogram equalization (HE), gamma correction (GC) where; white balance is for color correcting, histogram equalization if for adjusting contrast, and gamma correction is used to lighten the dark regions. In our work we are using one of the white balance method i.e. gray world algorithms which assume that the pixels are neutral gray on average because there is good dispersal of colors in the image. In our study we use an improved version of histogram equalization in our work i.e. contrast limited adaptive histogram equalization (CLAHE) algorithm. It also prevents over amplification of noise.

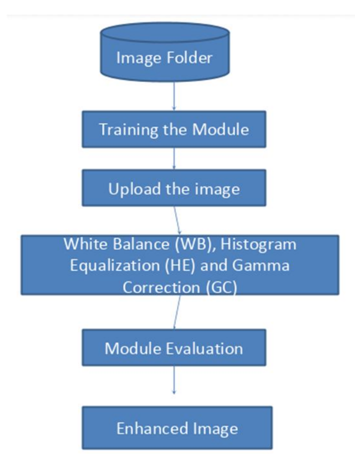

Figure 4.1: Design steps

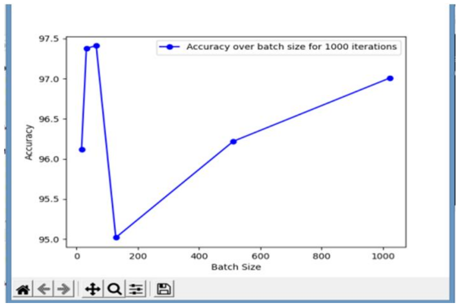

Figure 4.2: Graphical representation of the Accuracy of the network

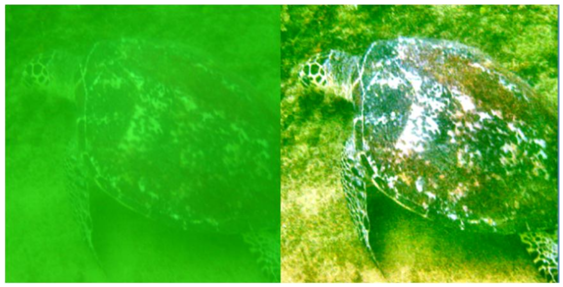

Figure (a): original picture and its improved version

Figure (b): original picture and its improved version

Figure (c): original picture and its improved version

Figure 5.1: Greenish degraded underwater images and their respected enhanced underwater images.

Further in module evaluation these images are compared with the trained module and try to do the computation pixel wise to improve the quality. Each pixel is processed and wherever the adjustment is needed in pixel reconfiguration, it is carried out and hence we get the enhanced image as a result.

Further the accuracy of the network is calculated as shown in Figure 4.2 by performing several iterations on different images with various batch sizes and the average of all these iterations is 97%. Hence the accuracy of this underwater image enhancement method is 97%.

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V. RESULTS

The primary purpose of underwater image enhancement is to restore the color, adjust the contrast, and adjust the brightness of the degraded underwater photographs. Following Figures 5.1 and 5.2 show the degraded underwater images on left side and enhanced underwater images on right side.

Figure (a): original picture and its improved version

Figure (b): original picture and its improved version

Figure (c): original picture and its improved version

Figure 5.2: Bluish degraded underwater images and their respected enhanced underwater images.

Table 5.1: Quantitative comparison of weekly supervised method and our method

Parameters	Weekly supervised method	Our method
Elapsed time	45.34s	35.628s
MSE	54986	46010
PSNR	7.345	9.2498
Accuracy	83%	97%

Table 5.1 displays the comparison of quantitative assessment metrics between powerful supervised deep learning method for underwater image enhancement and existing weekly supervised learning techniquesfor underwater image enhancement, in terms of elapsed time, MSE, PSNR, accuracy. Quantitative evaluation demonstrates the effectiveness of our work. From the above table it is clear that our work for enhancing the underwater images using powerful supervised learning method outperforms existing weakly supervised learning methods.

VI. CONCLUSION

In this work a powerful supervised deep learning approach is utilized for purpose of improving underwater photos. i.e. very deep super resolution (VDSR) model is investigated and applied. A large scale underwater image collection is undertaken and Convolution neural network (CNN) is used for training. When the system is trained, however, VDSR may improve qualities the underwater pictures in terms of color, contrast and brightness by utilizing different algorithms such as Adjusting white balance, histogram level, as well as gamma respectively. Outcome demonstrates that the method can improve underwater pictures. In future the more sophisticated underwater scenarios can be considered as well as underwater video augmentation by separating it into frames.

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