International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-10, August 2020

Deep Submerged Image Enhancement and Restoration Process using CNN

C.Raveena, Sri Kalaivani.R , Yagna.B , Rakshitha.T.R

***Abstract:** In oceanographic studies, underwater imagery plays a vital role. Underwater imaging has some of the advanced applications such as hand-held stereo-cam, fish-pond monitoring, etc. The majorsources of quality degradation in most of the underwater imaging processes are scattering and absorption which occurs due to light assimilation. In this paper, we propose a two step-strategy in which the former is the enhancement process and latter is the restoration process. Our unavoidable selective and quantitative appraise uncover that our upgraded pictures and recordings have better accessibility in the dark locales, progressed global and local contrast and better edge sharpness. In order to get rid of image quality impairments, we follow a method which involves only a single image. The major advantage of this method is that it does not require a specialized image-capturing equipment. Moreover, our substantiation gives a better accuracy by deploying Convolutional Neural Network(CNN) algorithm.*

***Keywords:** CNN, haze removal, colour correction, underwater image enhancement*

I. INTRODUCTION

Obtaining clear-cut impression in submerged condition is a significant problem in oceanographic studies. The nature of submerged pictures plays an imperative part in logical operations like observing ocean world, taking a count on population and surveying geographical and biological environments. Taking pictures in submerged condition is more challenging, mainly due to murkiness which is brought by sunlight that is reflected from a surface, and is also redirected and dispersed by submerged water particles and colour alter caused by fluctuations in light attenuation for various degrees of wavelength. Scattering of light and colour changes end in colour deviation and loss of contrast in underwater images. Haze is caused by suspended particulate matter like minerals, sand and tiny fishes which lives in oceans, streams and lakes. As light reflected from these objects propagate towards the capturing equipment, some of the sunlight meets the suspended particulate matter which in turn absorbs and scatters the light beam. Without the blackbody radiation, the light beam gets scattered into uniform back ground light at the instant of the multiple scattering process.

Revised Manuscript Received on August 30, 2020.
* Correspondence Author
C.Raveena*, Assistant Professor, Department of ECE, R.M.D. Engineering College, Chennai-601206, Tamilnadu, India. E-mail: cjraveena@gmail.com
R.Sri Kalaivani, Department of ECE, R.M.D. Engineering College, Chennai-601206, Tamilnadu, India. E-mail: srikalaivani7@gmail.com
B.Yagna, Department of ECE, R.M.D. Engineering College, Chennai-601206, Tamilnadu, India. E-mail: yagnab35@gmail.com
T.R.Rakshitha, Department of ECE, R.M.D. Engineering College, Chennai-601206, Tamilnadu, India. E-mail: rakshithatrhsr@gmail.com

Usually, the underwater image preparation centres exclusively on compensating either colour change distortion or light scattering. Strategies focussing on ejection of sunlight scattering distortion includes deceiving the effect of polarization to catch up the visibility degradation, to improve the clarity of images by using image dehazing, and combining modulation transfer function to reduce blurring effect. Eventhough the fore mentioned methods can increase the visibility and upgrade the scene contrast, but due to the difference in wavelength attenuation, distortion is caused but the colour change prevails to be imperforate. On the other hand, in order to evaluate the underwater haze-causing parameters, several colour correction methods are carried out, by utilizing histogram equalizations in both HIS and RGB to adjust the brightness distribution. And to compensate colour loss, controllable multicolour light source is utilized. Inspite of these enhanced colour balance, these strategies are incapable of ejecting the blurriness of the image caused by scattering of light. Because of these impacts an efficient method is required to take into account all these factors concerning colour change, light scattering and conceivable presence of artificial light source.

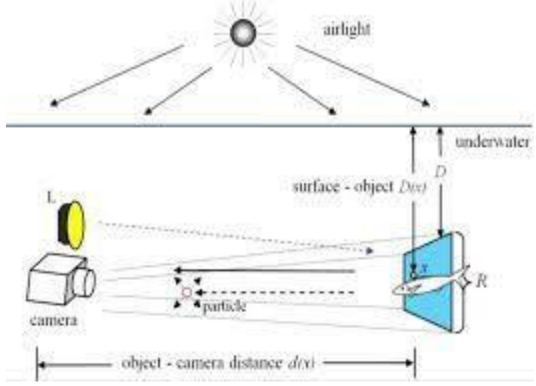

Fig 1. Sunlight enters from air to an underwater scene point

Convolutional Neural Network (CNN) removes multilations caused by light scrambling and colour alter. An existing scene depth induction strategy known as Dark Channel Prior is utilized to gauge the separations of underwater objects to the image capturing equipment. The low intensity within the dark channel is basically due to these three variables: 1) shadows, e.g., the shadows made by little fish, plants, animals or rocks in seabed, 2) dark objects, e.g., stone and dark animals and 3) colourful objects, e.g., ruddy or yellow sands, green plants, and colourful minerals/rocks, lacking in certain colour channels. Based on depth outline determined, the frontal area and foundation regions inside the images are sectioned.

The foreground and background light intensities are then contrasted to decide whether a man-made light source is utilized for image acquiring process.
If so, it is used and detected, then the brightness introduced by this lighting is ejected from the frontal area to maintain a strategic distance from over compensation in further steps. Next, fusion process and CNN algorithm are used to dispose the colour change and murkiness effect along the submerged propagation path towards the capturing equipment. Residual energy ratio among the diverse colour channels in BL is utilized to access the water depth inside a submerged scene. For each colour channel, the energy compensation is administered to regulate the natural colour of a scene. With the help of fore-mentioned method, stereo image sets or costly optical instruments are not required. This can viably upgrade visibility and re-establishes the underwater colour balance to give high colour constancy and perceptual clarity.

II. LITERATURE REVIEW

Different techniques are utilized for enhancing submerged images. Some of them are examined beneath.

A. Underwater Image Restoration Based on Light Absorption and Image Blurriness

The best strategy suitable for image restoration under the degree of blurriness and light absorption is the deep estimation method. This strategy was established by Ya - Tung Pend. This method can be used in the IFM to upgrade and restore the degraded submerged images. Here the color channel is not fixed as a frame of reference to estimate the scene deepness. Thus, this ends up in a proper image restoration process. This method first of all focusses on the blurred regions. From these locales, BL is selected. Then from the source of BL, transmission map and the depth maps are obtained which are impertinent for the restoration process. An important measure of depth is murkiness. But depth is not evaluated based on blurriness alone, both light assimilation and image haziness are also taken into account. The blurry regions are the source of the candidate BL which is employed in the determination of the blurriness BL. From this deep estimation is facilitated. The light beam travels a larger distance especially in the water and due to this far traveling, it gets absorbed by the light. Man-made lighting is rarely used to give adequate light for submerged videos and images. But it forms a bright foreground. Due to the presence of the foreground objects, this light gets reflected. It ventures less scattering and absorption. Misleadingly by using a building strategy, the bright foreground pixels are quite improved than the background pixels. The depth estimation of the red channels results in a maximum accuracy of bright pixels and does not over-remunerate the color. This occurs when the restoration process is accomplished by BL with diminishing counterfeit lighting. The scene depth would be effectively deciphered when there is brighter BL than the foreground pixels. In this case, there will be lesser red-light emission from the background pixels. This mechanism is one of the best-suited strategies to create a better enhanced and restored image even under various submerged lighting conditions and color tones.[2]

B. Low Complexity Underwater Image Enhancement Based on Dark Channel Prior

To upgrade the color contrast of the submerged images Hung-Yu Yang designed a DCP dependent least complex and underwater image upgrading technique. This method follows two ways. First, DCP is calculated for evaluating the air light and a deep map is produced by using a median filter. Second, a color correction technique is utilized for further gradation of the visual of the submerged images.

The atmospheric light is evaluated by using DCP. In DCP, the low intensity is principally due to color. A soft matting algorithm is used to reconstruct a quality image that will remove the transmission block effect. To solve the issues of bulky computing and several repetitions of optimized and smoothing transmission the median filter is used. In the dark channel, the top most splendid pixels are chosen and among these, the pixels with elevated intensity are chosen as atmospheric light. After that, a color correction technique is utilized. In submerged images, concerning other colors, the blue color is high which is utilized to increase the red and green colors to make the image stabilized. The preeminent blue color is set as mean and resting color channels are resolved with a multiplier to obtain color stabilized images.[3]

C. Underwater Image Enhancement by Wavelet Fusion

To upgrade the murky submerged pictures Amjad Khan designed a wavelet-based combination strategy by pointing color alternate and low contrast issues. At first, the hazy based submerged picture is reproduced into two classes. These classes are prepared in corresponding to increase the image contrast and quality. Contrast Limited Adaptive Histogram Equalization is a form of AHE. A series of high and low pass filters are used for the wavelet-based fusion process. They are embraced to improve the complexity and nature of submerged images by clipping the unwanted regions from the histogram. The cutting limit is characterized by the histogram standardization and the size of the local districts inside the pixel domain. The piece of the district is not disposed of yet it is equally redistributed among all the histogram bins. Then the CLAHE is tested to all color channels i.e., red, green, and blue to increase the contrast of all shades present in the picture.

An arrangement of high and low pass filter is used to take out high and low frequency contained in the image and to make the merging procedure helpful. For decomposition two levels are employed. In the first level, the following two stages are done; the initiatory step is done by using the high and low pass filters alongside down-sampling on input image particularly in the rows. In this manner, parallel closeness and even subtleties are obtained. After that, in the level coefficient, the columns are down-sampled and filtered similarly. At the next level of deterioration, the disintegrated close image of the column turns into the input. The coefficients are scale downed by the rehashing technique. By using the same technique each of the input pictures is reduced into wavelet coefficients.

Finally, both the reductions are combined by utilizing coefficients of maximum value.[4]

III. PROPOSED METHODOLOGY

The significant reason for decline in the image quality is due to absorption and scattering effects in underwater. Specialists experience incredible troubles in capturing the underwater images. Hence, it of great importance to improve the quality of submerged images prior to its degradation. Our methodology provides a haze- free image with the employment of just a single picture captured from a conventional camera. We categorize the quality improvement strategies for submerged images as image restoration methods, by utilizing CNN calculation from the point of view that these improve picture quality either through the optical imaging physical model or not.

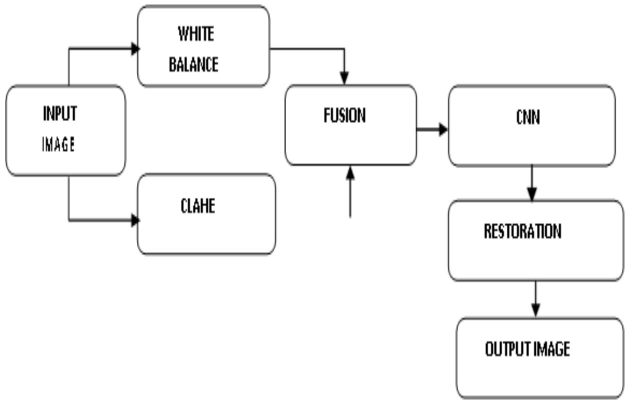

Fig 2. Block diagram of proposed method

A. Image Acquisition

To manage pictures and before examining them the most significant thing is to catch the picture. This is called as Image Acquisition. Digital imaging or digital image acquisition is that the arrangement of a deliberately encoded depiction of the visual characteristics of a thing, like a physical scene or the inside structure of an article.

B. Underwater White Balance

Our image processing methodology employs two phases. White balancing and image fusion processes takes place in the former phase, to improve the quality of the underwater images. In underwater images, one of the most important problem is the bluish-green appearance. In order to resolve this problem, we choose white balancing process which improves the image aspect by cancelling the unmatched colour castings.

Four principles have been constructed to compensate the red channel loss which is as follows:

1) The channels with colours such as green have lesser wavelength and moreover these lights while travelling underwater are preserved form being lost but whereas red and blue color channels are lost while travelling on clear water due to longer wavelengths.
2) Green channels are the ones which gives us the exact background color information with high accuracy rather than any of the color channels say red channel and so it is impertinent to make a flare compensation in the use of red channels to acquire the accurate information. In order to make the compensation of red channel attenuations we implement the idea of adding a part of the green channels to the red ones. Earlier we tried by adding both the fractions of blue and green to it, but the results were not satisfactory and moreover adding only the fractions of green channels resulted in achieving a more natural appearance of the water regions or of the background.
3) The difference between the means of the green and red values should be in proportion with the compensation made to explicitly out show the disparity between those two channels.
4) While performing red channel compensation, steps should be taken to avoid the red channel saturation. This implies that the enhancement of the red channels should not change the pixel values of an already significant red components rather it should change pixels values of those of the smaller red channel. This could be illustrated in another way i.e., the information of the green channels shouldbe transferred only to the red channels that are not significant. Thereby it is impertinent to make the red channel compensations in the areas of high attenuations and also in the over exposed regions. The above statements reveal that when the location is nearer to the observer, then the pixels seems to have significant values of all the three channels namely red, blue and green.

C. CLAHE

Histogram equalization (HE) is one of the image enhancement method which results in an enhanced image quality without any loss of information irrespective of the source of degradation. HE makes the image contrast adjustment to bring out the images with impeccable clarity. Through this contrast adjustment, the intensities can be better redistributed. By the use of this HE functions the original histogram can be recovered. This HE allows regions of lower contrast to gain higher contrast. This is made effectively by spreading out the most frequent intensity values. The major disadvantage of this method is that this approach is inappropriate for a general improvement, however neighbour-hood subtleties are not featured. Adaptive Histogram Equalization (AHE) is an image processing technique which is used to improve the contrast in images. Several histograms are computed by AHE where each corresponds to distinct section of the image. It improves both the local and the global contrast and it highly defines the edges of each locales of the image. Normally AHE has the tendency to over-amplify the noise. In order to sort out this problem we choose Contrast Limited Adaptive Histogram Equalization (CLAHE) which limits the above effect. It is done by clipping the histogram at some already predefined value which is normally done before the computation of Cumulative Distributive Function (CDF). It is advantageous because it does not discard the histograms that exceeds the clip limit but equally redistributes it among all the histograms.

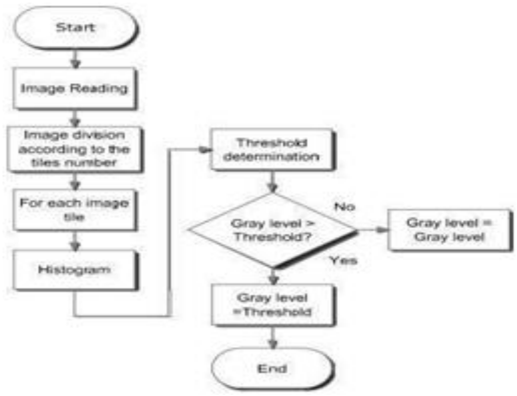

Fig 3. Flowchart for CLAHE

D. Multiscale Fusion

Fusion process is an approach which increases scene visibility of an image even under a severely degraded environment. This step is nothing but the combination of several input images into a single output image. The main aim of this fusion stage is to deliver a haze-free image with high clarity and accuracy for human visualization. Hereby, fusion process is performed to combine the white balanced image (Fig 7) and the CLAHE applied image (Fig 8) in order to generate output image with better visibility. Then unsharp masking (USM) is implemented for image sharpening. From the input images of the fusion process weight maps are derived to overcome the artifacts. Here linear fusion is implemented, which can be illustrated with help of the linear equation mentioned below:

$$I_{enhanced} = \alpha * A + (1-\alpha) * B \quad (1)$$

where α is a constant. It ranges from 0 to 1. Let A and B denote the degraded underwater images applied with CLAHE and USM respectively.

E. Convolutional Neural Network

In order to improve the image contrast and color cast, a CNN based image restoration method is likely to be deployed. Like most of methods, the unknown parameters can be estimated respectively. The CNN architecture of our approach is presented in Fig 4. It consists of three modules: A-network, T- network, and J- estimator. Global ambient light is estimated by the A-network. Also, the T-network is utilized to gauge blue channel transmission map of the submerged image. Then, the image is finally restored in J-estimator module.

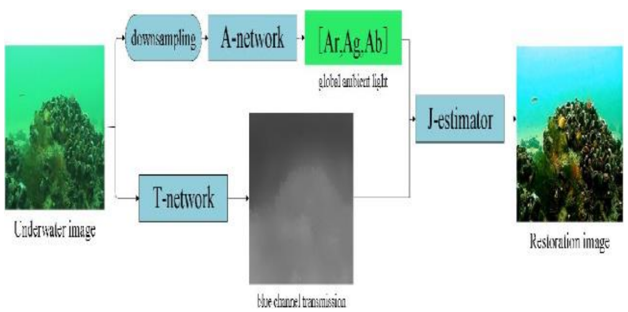

Fig 4. CNN Architecture

A-network: As referenced previously, most of the conventional ambient light estimation techniques select pixels with interminable depth to assess ambient light. Camera angle is the only limiting factor when it comes to selection. To resolve these issue we learn the mapping between the underwater images and the ambient light and this in turn improves the robustness of our estimation.

Fig 5. The architecture of A-network

The A-network architecture is given in Fig 5. A-network majorly consists of two operations. One is convolution another one is max-pooling.

T-network: Recently, several CNN architectures were proposed on similar topics for estimating one channel transmission map. They assume that transmission of the three channels is the same. However, the assumption fails in the issue of submerged image restoration. We have to evaluate three channel transmission separately. For reducing intricacy of training, we check the blue channel transmission by CNN. So, we simplify the problem to one channel transmission estimation problem. Since Ic(x) is subject to tc(x) as indicated by Ep (1), we build a CNN model, and train the model by limiting the reconstruction errors between its output tb(x) and the ground truth blue channel transmission map.

J-estimator: tg(x) and tr(x) are recovered from assessing A-network's Ac and from T-network's tb(x) respectively. Then, as indicated by scene radiance can be re-established as follows:

$$Jc(x) = (Ic(x) – Bc) / tc(x) + Bc \quad (2)$$

IV. RESULTS

The simulation results shown below corresponds to the step-wise output of our proposed approach. The process is tested with the help of some underwater net images. Filters and histogram equalizers are used to get rid of noise and to give an enhanced quality image as the output. All these simulations are done in MATLAB platform. The input images appear to be bluish because of the underwater environment and the scattering effects. From each step of the enhancement process weight maps are derived and a normalized weight is estimated according to which the output image should be in correspondence. Fig 6 refers to the image which is given as the input. This is nothing but the images acquisition process. Right from the input image weight maps are derived in order to get an enhanced image at the end. The input image is overwhelmed by dark areas which are to be corrected to the normal contrast. Fig 7 corresponds to the white balanced image which improves the image aspect to the greater extent. CLAHE is applied to the input image and the resultant is Fig 8. This step increases the image visibility by enhancing all the local regions and delivering the useful information by increasing the pixel concentration of the histograms.

The enhancement stage comes to an end by the deployment of the fusion process which is shown in Fig 9. Here, this process combines the white balanced image and the CLAHE applied image. And the latter step, restoration process which employs the use of CNN algorithm to restore each and every pixel and abruptly eliminates all the degradations to achieve a better performance is shown in Fig 10.

Fig 6. Input image

Fig 7. White balanced image

Fig 8. CLAHE applied image

Fig 9. Fused image

Fig 10. Restored image

De-noising Performance

De-noising performance is carried out to investigate the effect of depth of the network. The table below illustrates that deeper network doesn't mean to give better performance. Meanwhile those even create some type of disturbances in the kind of noise. So, we chose with 3 conv-3 deconv networks instead of 5 conv - 5 deconv network according to the following analysis made as mentioned in the table.

TABLE 1. The performance of various network configurations.

	SSIM	PSNR
2con-2decon	0.7202	24.3907
3con-3decon	**0.7498**	**25.1066**
5con-5decon	0.6755	23.5627

V. CONCLUSION

In this paper an image processing-based approach is proposed for an underwater image enhancement and restoration. The proposed approach is based on Convolutional Neural Network algorithm. As mentioned earlier our approach is a two step-strategy in which the enhancement step employs the fusion process and the restoration process employs the CNN which is a multi-layer neural network to process the 2- D images. The outcome is of good quality and gives better edge sharpness. This underwater imaging method has a major role in various field of applications such as seabed exploration, inspection of coral reefs and in the study of marine organisms. In future, this work can be extended to high-level feature analysis such as target detection even under severely degraded underwater environments.

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AUTHORS PROFILE

Ms. C. RAVEENA, B.E., M.E., is an Assistant Professor in Department of Electronics and Communication Engineering, since June 2012. She obtained her B.E (ECE) from Noorul Islam College of Engineering and M.E (Network Engineering) from Arulmigu Kalasalingam College of Engineering. She has been in the teaching profession for the past 11 years and has handled UG programs. Her areas of interest includes Network security and management,
Security and Mobile Ad-hoc networks. She has published 3 papers in International journals and presented 2 papers in National Conferences. She is a life time member of ISTE, SDIWC, IAENG. She has attended many workshops & FDPs sponsored by AICTE related to her area of interest. **cjraveena@gmail.com**

R. SRI KALAIVANI, B.E., is pursuing her degree in Electronics & Communication Engineering from R.M.D. Engineering College, affiliated to Anna University, Chennai. She presented a paper in Anna University and done a project on “Intelligent brake control system”. Her area of interest includes Deep learning and Image processing. **srikalaivani7@gmail.com**

B. YAGNA, B.E., is pursuing her degree in Electronics & Communication Engineering from R.M.D. Engineering College, affiliated to Anna University, Chennai. She presented a paper in Anna University and done a project on “Underground cable fault detection”. Her area of interest includes Deep learning and Image processing. **yagnab35@gmail.com**

T.R. RAKSHITHA, B.E., is pursuing her degree in Electronics & Communication Engineering from R.M.D. Engineering College, affiliated to Anna University, Chennai. She has done a project on “Bus tracking system using RFID”. Her area of interest includes Deep learning and Image processing. **rakshithatrhsr@gmail.com**