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Underwater Image Enhancement Using Deep CNN Based Multi-Scale Fusion and Optimized ULAP Based Depth Estimation

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ABSTRACT
In this paper, the underwater image enhancement is done by the developed model, namely Deep Convolutional Neural network (CNN)-based multi-scale fusion with Optimized Underwater Light Attenuation Prior (ULAP) technique. Here, the white balancing image is done and the multi-scale fusion is carried out using Deep CNN based on the normalized weight of images. Moreover, the blur detection and estimation process is completed using Laplacian's variance method. In addition, the depth estimation is carried out using optimized ULAP and image deblurring is done by adaptive feature fusion CNN. In addition, the pixel enhancement is done by the statistical model, namely Type 2 fuzzy and cuckoo search-based filter (T2FCS filter). The final image fusion is done by combining the multi-scale fused output of Deep CNN and the output of optimized ULAP-based enhancement. Moreover, the experimental result demonstrates that the developed model attained the Peak signal to noise ratio (PSNR) is 40.05, Mean square Error (MSE) is 2.846, structural similarity index measure (SSIM) is 0.931, underwater color image quality evaluation function (UCIQE) is 0.900 and Underwater Image Quality Measures (UIQM) is 5.816, correspondingly.
***Keywords:** : Laplacian's variance method, Underwater Light Attenuation Prior, Deep Convolutional Neural network, Type 2 fuzzy and cuckoo search-based filter, Gray-World algorithm.*

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INTRODUCTION

The underwater environment provides various rare attractions, like fishes and marine animals, mysterious shipwrecks and amazing landscapes. Moreover, underwater imaging technology provides a major role in underwater imaging applications, such as analysis off underwater environments, cables, monitoring of underwater vehicles, archaeology, marine biology analysis and manmade object detection. However, the underwater images are affected due to the attenuation of propagated light, which reduced the visibility of images. In addition, the scattering and absorption effects are the two important factors for reducing the visibility of underwater images. The absorption effect diminishes the light energy, whereas the scattering effect make changes in the direction of light propagation. The important factors, which affect the quality of images are foggy appearance, misty and contrast degradation. Generally, the underwater image with the objects more than 10 meters is very difficult to perceive and they faded the colour of objects based on the depth of water. There are various approaches are invented by investigators for improving the quality of degraded images. In addition, the underwater image deterioration processes are derived by combining additive, multiplicative and traditional enhancing approaches, like histogram equalization and gamma correction in order to generate the enhanced images [8]. For improving the visibility of underwater images, underwater sharpening approaches have been utilized, such as underwater image enhancement techniques, underwater image restoration techniques and data-driven techniques. In restoration techniques, the affected physical model has been considered for restoring the underwater images. However, this technique is inflexible and not accurate due to the distinct complicated underwater objects. Enhancement techniques are achieved by adjusting the pixel values in order to improve the quality of underwater images without utilizing the excess parameters. Though the enhancement approaches are flexible and fast processing, this tends to be under-enhanced or over-enhanced due to the fault of selecting underwater optical imaging parameters. Data-driven approaches are learned by the synthetic pairs of corrupted images and maximum-quality counterparts. Moreover, the data-driven approaches are mainly depending on the huge amount of training data and difficult structure of network model. Especially, the underwater image enhancement approaches enhance the brightness and contrast of underwater images by adjusting the pixel values of images. Polarization-based techniques are the most widely used image restoration technique. Some of the widely utilized pixel enhancement approaches are Retinex-based techniques, histogram-based techniques, fusion-based techniques and other techniques [13]. The main aim of this research is to design and develop the Deep CNN-based multi-scale fusion+ULAP technique for performing the multi-scale fusion. Initially, the white balancing process is applied to the input image such that the two white balanced images are produced, such as the gamma corrected image and sharpened image. After that, the weight map and normalized weight is computed from the gamma corrected image. Similarly, the weight map and normalized weight is computed from the sharpened image. After that, the multi-scale fusion is carried out to combine the normalized weight of both gamma corrected image and sharpened image using Deep CNN. On the other hand, the input image is applied to the blur detection, and estimation process is carried out by Laplacian's variance, and then the depth estimation is done using optimized ULAP. After that, the image deblurring is carried out using adaptive feature fusion CNN in order to remove the blur exist in the image. After the completion of deblurring, the pixel enhancement is carried out using T2FCS algorithm. At last, the final fusion is done by combining the output of multi-scale fusion and the output of optimized ULAP-based enhancement.

The major contribution of this research is,

- ***Proposed Deep CNN-based multi-scale fusion+ULAP for image enhancement***: In this research, the image enhancement is done using developed Deep CNN-based multi-scale fusion+ULAP technique. Here, the image enhancement is done by fusing the multi-scale fused output of Deep CNN and the output of optimized ULAP-based enhancement.

The organization of this research paper is given below. Section 2 describes the literature review of this paper, section 3 portrays the developed method, section 4 describes the results and discussion of developed model and section 5 portrays the conclusion of this paper.

The literature review of various techniques based on underwater image enhancement is given below. Codruta O. Ancuti *et al.* [8] developed the multi-scale fusion technique for performing the underwater image enhancement. Here, the image enhancement strategy was carried out based on two steps, such as white balancing and image fusion. The white balancing approach was employed to enhance image characteristics by eliminating the irrelevant colour castings. In addition, the multi-scale fusion was carried out using the Naïve fusion scheme. However, the processing speed of this method was high. In order to reduce this, FarongGao *et al.* [14] modeled the multi-scale fusion process for performing the image enhancement. The processing steps involved in the developed model were image compensation, image sharpening and image fusion. The image compensation was carried out based on the red channel, whereas multi-scale fusion process was employed to fuse the local contrasted image and sharpening image. Moreover, this method was suitable for applying various environments without affecting the image quality. However, the processing time of this method was low. In order to improve the processing time, Chongyi Li *et al.* [12] devised the Underwater Convolutional Neural Network (UWCNN) model for improving the image and video quality. Here, the developed UWCNN model was devised by including an enhancement unit with the CNN model. Moreover, this method may produce network loss, which degrades the performance of the system. In order to avoid network loss, Linfeng Bai *et al.* [13] introduced the multi-scale fusion process for enhancing image quality. Here, the processing was done using four stages, such as center regionalization of pixel intensity, histogram global equalization, histogram local equalization and multi-scale fusion. The first stage was employed to perform the image histogram centralization, the second step was utilized to adjust the colour of an image, the third step was employed to improve the contrast of an image and the final step was employed to fuse the contrast and color corrected image with the weight maps. However, this method was failed to identify the exact consistency of background images.

Challenges

The challenges faced during the analysis of various underwater image enhancement methods are given below.

- In [12], the developed model was processed only one model for predicting the output in order to attain the image enhancement. Moreover, this method was considered the low contrast indoor training data for processing. Thus, the challenge lies on improving the performance of UWCNN model.
- In order to enhance the performance, four-stage multi-scale fusion process was introduced in [13]. This method did not provide the accurate consistency of background in the same scene at different cameras. Moreover, the computational complexity of this method was high.

- For improving the image quality and reducing the computational complexity, multi-scale fusion was implemented in [14]. This method did not provide the better result with motion-blurred image and it was failed to suppress the light produced by scattered speckle interference.

MATERIAL AND METHODS

Proposed Underwater image enhancement based on multi-scale fusion

This section describes the block diagram of developed Deep CNN-based multi-scale fusion+ULAP for underwater image enhancement based on multi-scale fusion. Initially, the weight map is calculated at the white balanced images, like gamma corrected image and sharpened image [8]. After that, the normalized weight is calculated for the weight map of two images. Once the normalized weight is calculated, then the multi-scale fusion is carried out using Deep CNN, such that the enhanced image is attained. On the other hand, the blur detection and estimation is carried out using Laplacian's variance and the depth estimation is done by optimized ULAP. Moreover, the process of deblurring is done using adaptive feature fusion CNN and the pixel enhancement is done by statistical model. Finally, the fusion process is done by the averaging model in order to attain the fused image. Figure 1 shows the block diagram of developed Deep CNN-based multi-scale fusion+ULAP

Generation of white-balanced image

The input image is applied to the white balanced image generation process, which generates the two processed images, such as gamma corrected image and sharpened image. The white balanced image generation [8] is used to resolve the color cast produced by the selective absorption of colors with depth. Moreover, the white balancing approach is used to enhance the image quality by eliminating the undesired color castings due to dissimilar illumination or the properties of medium attenuation. In deep water, the color intensity of image is highly affected due to the depth, which produces the green-bluish appearance on the image and it needs to be removed. In order to achieve this, white balancing approach is applied to eliminate the bluish tone on the image, and this produces some red artifacts. The red artifacts are produced due to the existence of the red channel. Hence, the red channel and blue channel are need to be compensate for attaining the white balanced image. Moreover, the expression for the red channel at pixel location is given by,

$$D_{rc}(u) = D_r(u) + \mu.(\overline{D}_g - \overline{D}_r).(1 - D_r(u)).D_g(u) \tag{1}$$

where, D_r and D_g demonstrates the red and green channel of an image, $\overline{D}_r$ and $\overline{D}_g$ indicates the average value of D_r and D_g, correspondingly. Moreover, the blue channel is computed by,

$$D_{bc}(u) = D_b(u) + \mu.(\overline{D}_g - \overline{D}_b).(1 - D_b(u)).D_g(u) \tag{2}$$

where, D_b and D_g deliberates the blue and green channel of an image, $\overline{D}_b$ and $\overline{D}_g$ shows the mean value of D_b and D_g, correspondingly. Once the red channel compensation is completed, then the illuminant color cast is estimated and then compensated. Moreover, the white-balanced images are represented as w_{b1}, which is utilized for further processing. However, white balancing may cause a noticeable effect at water depth more than 30ft, since the absorbed colors are very difficult to identify in deep water. Hence, gamma correction provides a better solution for this issue, which is described as below.

Construction of Sharpened and Gamma corrected images

The generation of white balanced image [8] improves the image appearance by eliminating the irrelevant color cast. Gamma correction process provides the dissimilarities among darker/lighter regions at the loss cost of underexposed and overexposed regions. For compensating the loss, unsharp masking principle is utilized, which converts the unsharp or blurred images into the shapen images. The advantage of gamma correction process is it does not need any additional constraints for training. The standard formula for unsharp masking principle at sharpened image S_D is given as,

$$S_D = D + \chi(D - G * D) \tag{3}$$

where, D denotes the sharpened image, $G * D$ indicates the Gaussian filtered version of D, and χ denotes the parameter. A smaller value of χ fails to sharpen the image, but the higher value of χ produces the over-saturated region with brighter highlights and darker shadows. In order to resolve problem, sharpened image S_D is computed as,

$$S_D = (D + N\{D - G * D\})/2 \tag{4}$$

where, $N\{.\}$ indicates the linear normalization operator, and the sharpened and gamma corrected images are represented as w_{g1}. After that, the white balanced image w_{b1} and gamma corrected images w_{g1} are forwarded to the weight map generation process for further processing.

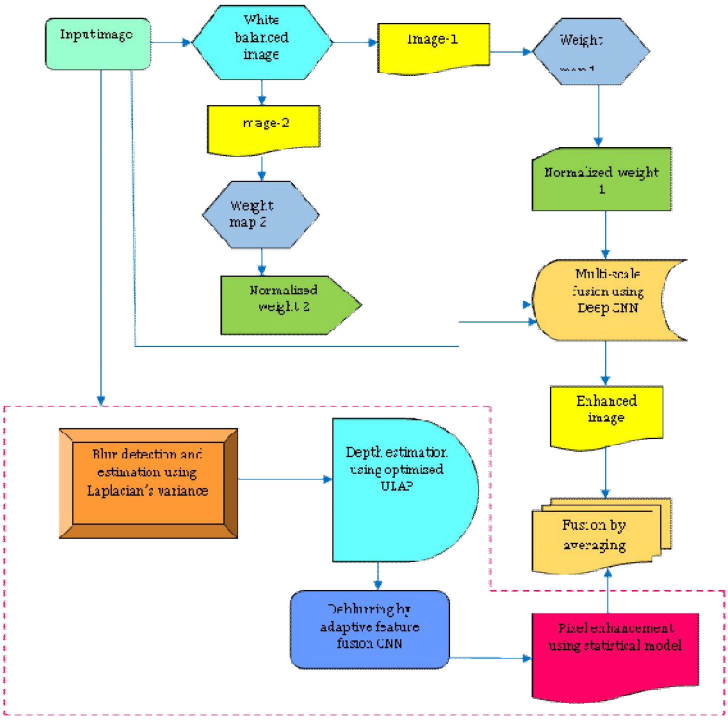


Figure 1. Block diagram of proposed Deep CNN-based multiscale fusion+ULAP

Weight maps for fusion

The input of weight map fusion process is white balanced image w_{b1} and gamma corrected images w_{g1}. The weight maps are utilized for joining the pixel with the maximum weight value in order to attain the final image [8]. The weight maps are calculated based on the saliency metrics, which are described as below.

Laplacian contrast weight (WL): It computes the global contrast by calculating the absolute value of Laplacian filter subjected to every input luminance channel.

Saliency weight (WS): WS is employed to emphasize the saliency objects that lose their eminence in the underwater scene. Here, the saliency level is estimated using saliency estimator, and the saliency map is used to highlight the vital region.

Saturation weight (WSat): WSat is employed to fuse the image by adapting the chromatic information from highly saturated regions. The weight map is computed between red, green and blue channels, which is expressed as,

$$\varpi_{satu} = \sqrt{1/3\left[(R_h - J_h)^2 + (G_h - J_h)^2 + (B_h - J_h)^2\right]} \tag{5}$$

where, R_h, G_h and B_h denotes the colour channels and J_h represents the luminance. Here, the normalized weight is calculated for two images, which is represented as w_1 and w_2 and is sent to the multi-scale fusion process.

Multi-scale fusion using Deep CNN

This section explains the multi-scale fusion based on Deep CNN. Here, the multi-scale fusion is carried out for the normalized weight-1 w_1 and normalized weight-2 w_2 with the input image. Deep CNN performs the multi-scale fusion by combining the normalized weights-1 and 2 with input image. The advantage of Deep CNN is that the processing speed of this method is high. The architecture of Deep CNN is given below.

Structural design of Deep CNN

The Deep CNN [9] comprises of three layers, such as Convolutional (conv) layer, pooling layer and fully connected (FC) layer. The advantage of Deep CNN is that the processing speed of this method is high. In Deep CNN, the feature map is constructed, sampled and is forwarded to the pooling layer.

(i) Conv layers:

In this layer, the feature map of normalized images are generated based on the centered unit (k, y) is portrayed as,

$$\left(H_d^f\right)_{k,y} = \left(m_d^f\right)_{k,y} + \sum_{q=1}^{z_1^{d-1}} \sum_{s=-p_1^d}^{p_1^d} \sum_{v=-p_2^d}^{p_2^d} \left(n_{f,q}^d\right)_{s,v} * \left(H_d^{f-1}\right)_{k+s,y+v} \tag{6}$$

where, $*$ indicates the convolutional operator, $\left(H_d^f\right)_{k,y}$ signifies the feature map of d^{th} conv layers, $\left(H_d^{f-1}\right)_{k+s,y+v}$ represents the rigid feature map of preceding conv layers which is centered at (k, y), $\left(m_d^f\right)_{k,y}$ represents the bias at d^{th} conv layers and $\left(n_{f,q}^d\right)_{s,v}$ represents the kernel function in w^{th} conv layers.

(ii) Pooling layers: The pooling layer refers to the non-parametric layer, which does not have bias or weights.

(iii) FC layers: The data collected from pooling layer is sent to the input of FC layer for fusing the normalized images, and its expression is given by,

$$c_d^f = \vartheta\left(S_d^{\,f}\right) with\, S_d^f = \sum_{q=1}^{z_1^{d-1}} \sum_{s=-p_1^d}^{p_1^d} \sum_{v=-p_2^d}^{p_2^d} \left(n_{f,q}^d\right)_{s,v} * \left(H_d^{f-1}\right)_{k+s,y+v} \tag{7}$$

Hence, the output attained from DCNN is the multi-scale fused images, which are represented as Z.

Optimized ULAP-based depth estimation and adaptive CNN-based image enhancement

This section describes the process of image enhancement, which involves three steps, such as blur detection and estimation and depth estimation and adaptive CNN fusion. Here, the blur detection and estimation is carried out using the Laplacian Variance approach, which involves two steps, such as laplacian kernel and thresholding. Depth estimation is done by optimized ULAP model and the image enhancement is carried out based on an adaptive CNN fusion. All of these processes are explained as below.

i) Blur detection and estimation with Laplacian Variance

The blur detection and estimation is carried out based on fused image Z using Laplacian Variance approach based on Laplacian kernel. The convolution of Laplacian kernel is carried out by performing the component-wise multiplication of two matrices followed by the summation of components. After that, the blur image is detected by the Laplacian Variance approach in which the variance is calculated based on the convolution of input images using Laplacian operator. In addition, the blurriness of the images is diminished by fixing the specified threshold value. If the threshold value is small, then the images are indicated as blur otherwise the images are represented as not blurry. Moreover, the blur matrix is represented as Q.

Depth estimation based on optimized ULAP model

The blur matrix Q is fed to the input of depth estimation process using optimized ULAP model [1], which is determined by calculating the difference among the value of R intensity (VR) , and maximum value of G-B intensity (MVGB).

Scene depth estimation based on optimized ULAP

In ULAP [1], the depth map is determined by evaluating the difference among MVGB and VR, which is portrayed as,

$$aa(cc) = \alpha\alpha_0 + \alpha\alpha_1 xx(cc) + \alpha\alpha_2 tt(cc) \tag{8}$$

where, cc represents pixel, $aa(cc)$ indicates the underwater scene depth at point cc, and $xx(cc)$ signifies MVGB, $tt(cc)$ denotes VR. The depth estimation output is signified as B.

Training model

This section explains the training process of Competitive Multi-Verse bird swarm Optimization (CMVBSO), which is used to train the coefficients α_0, α_2 and α_3, correspondingly. Moreover, the

CMVBSO algorithm is designed by the incorporation of CMVO [2] and BSA [3]. The final updated equation of CMVBSO algorithm is given by,

$$Q_{e,o}^{l}=\frac{1-rand(0,1)(U+V)}{1-rand(0,1)(U+V)+L_2+L_3}\left[\frac{L_1*TDR+L_2*W_{j,o}+L_3*W_o+\dfrac{(F_{e,o}\times U+i_o\times V)rand(0,1)}{1-rand(0,1)(U+V)}}{(L_2+L_3)}\right] \tag{9}$$

where, $rand(0,1)$ denotes the random number ranges between o to 1, V and U signifies the social accelerated and cognitive coefficients, $F_{e,o}$ denotes the optimum preceding location of e^{th} solution, i_o denotes the optimal preceding location of swarm, and $W_{j,o}$ specifies the global loser in o^{th} round of competition, W_o denotes the average location of appropriate universe, TDR depicts the coefficient, and L_1, L_2 and L_3 denotes the random numbers among [0, 1].

Deblurring using adaptive feature fusion CNN

In deblurring, the blur matrix Q, Depth estimation output B and the input image set is selected as an input and the processing is carried out using adaptive feature fusion CNN. Fully Convolutional Neural Network (FCNN) avoids the use of dense layers, which utilizes minimal parameters and the training speed of this network is high.

a) Adaptive Feature Fusion with FCNN

The FCNN [4] contains five pooling layers. After the completion of pooling at five times, then the pixel density is reduced by 2, 4, 8, 16 and 32 times in a series, thereby the image is to be blurred. In order to attain the improved outcome, the feature maps of dissimilar layers are joined with dissimilar weights. Moreover, the expression for FCNN is given by,

$$P=T_3*up(pool3)+T_2*up(pool4)+T_1*up(conv7) \tag{10}$$

$$\{T_1,T_2,T_3\}=f(trn) \tag{11}$$

where, $up(*)$ symbolize upsampling function, T_1,T_2,T_3 signifies weights where different layers contribute in fusion, z refers output of network, and $f(.)$ signifies function where fusion coefficients alters with present training, and trn signifies current count of training

b) MRFLO-based training

The training process of FCNN is carried out using MRFLO algorithm for deblurring the frame. The developed MRFLO algorithm is designed by the integration of Manta Ray Foraging algorithm (MRFO) [5] and Lion Optimization Algorithm (LOA) [6]. Here, MRFO algorithm is designed based on the cyclone foraging behaviour, whereas the LOA is designed based on the hunting activities of lions. Moreover, the final updated equation of MRFLO algorithm is given below.

$$A_C^{i+1}=\frac{1-0.1E_1E_2+0.05E_1}{\left[(1-0.1E_1E_2+0.05E_1)+\left(E+e^{M\omega}\cos(2\pi\omega)\right)\right]}\left[A_{best}\,[1+e^{M\omega}\cos(2\pi\omega)]+\left[\frac{A_C^{best}(0.1E_1-0.05)}{1-0.1E_1E_2+0.05E_1}\right]\left(E+e^{M\omega}\cos(2\pi\omega)\right)+E\,A_{C-1}^{i}\right] \tag{12}$$

where, ω, E_1 and E_2 denotes the random numbers lies between 0 and 1, A_C^i denotes the element of C^{th} vector of $Y^{female+}$, C represents the arbitrary integer lies between 1 and I, and A_{best} indicates the plankton with high concentration, and A_C^{best} denotes the best component of C^{th} vector.

Pixel enhancement based on T2FCS filter

After the completion of image deblurring, the noisy pixel exist in the image is enhanced using T2FCS filter [7]. For instance, if the noise exists in the pixel is located at center, then it is replaced with new pixel, which is expressed as,

$$Y^*(g,n)=\frac{\sum(Y(g,n).\rho(g,n))}{\sum\Re(g,n)} \tag{13}$$

where, $Y^*(g,n)$ indicates new pixel value. Hence, the new pixel value is calculated with T2FCS filter in order to improve the value of the pixel based on image. Thus, the final outcome of image enhancement process is represented as Y^*.

Image fusion

The final phase of this paper is the feature fusion process. Here, the final image fusion is done by summing the multi-scale fused output and optimized ULAP output, which is given by,

$$F = \beta Z + (1-\beta) Y^* \tag{14}$$

where, Z denotes the output of multi-scale fusion using Deep CNN, Y^* represents the outcome of optimized ULAP-based enhancement and the value of α is 0.7.

RESULT AND DISCUSSION

This section explains the results and discussion of developed Deep CNN-based multi scale fusion+ULAP for underwater image enhancement.

Experimental setup

The implementation of developed algorithm is done in Python tool with windows 10 OS, 4GB RAM, and Intel processor.

Dataset description

The dataset employed for the experimentation of the developed method is Underwater Scene Prior Inspired Deep Underwater Image and Video Enhancement dataset (Dataset-1) [10] and An Underwater Image Enhancement Benchmark Dataset and beyond dataset (Dataset-2) [11].

Dataset-1: Dataset-1 comprises the coastal and oceanic water classes. For coastal class, type-1 water signifies the clearest water and type-II denotes the turbid open ocean water. For oceanic class, type-1 water signifies the clearest water and type-II denotes the most turbid. Moreover, the type-1 images are considered for the experimentation process. In this research, only the images are considered as an input for further processing.

Dataset-2: Dataset-2 comprises 890 high-quality underwater images and 60 challenging underwater images.

Evaluation metrics

The evaluation metrics employed for the experimentation of developed are PSNR, MSE, SSIM, UCIQE and UIQM.

PSNR

The PSNR is the proportion of the maximum signal power to the noise power. The PSNR is computed as follows,

$$PSNR = 10\log_{10}\left(\frac{m_{\max}^{2}}{MSE}\right) \tag{15}$$

where, the mean square error is indicated as MSE, and maximum signal power is represented as $m_{\max}$.

MSE

The cumulative squared difference among the fused and original image is defined as MSE. The MSE is computed as below,

$$MSE = \frac{\sum_{N,E}\left[A_1(n,e) - A_2(n,e)\right]^2}{N * E} \tag{16}$$

where, fused and original image is indicated as A_1 and A_2 respectively, the image with row and column is signified as N and E, correspondingly.

SSIM

The similarities between fused and original image is measured using SSIM.

$$SSIM(\mu_1,\mu_2) = \frac{(2\delta_{\mu_1}\delta_{\mu_2} + e_1)(2\sigma_{\mu_1\mu_2} + e_2)}{(\delta_{\mu_1}^{2} + \delta_{\mu_2}^{2} + e_1)(\sigma_{\mu_1}^{2} + \sigma_{\mu_2}^{2} + e_2)} \tag{17}$$

where, the mean pixel value at μ_1 and μ_2 are signified as δ_{μ_1} and δ_{μ_2}, variance of pixel is indicated as, σ_{μ_1} and σ_{μ_2}, the stabilizing division of denominator is represented as, e_1 and e_2.

UCIQE

The UCIQE of developed method is computed using the below expression as,

$$UCIQE = c_1 \times o_c + c_2 \times con + c_3 \times \varphi_l \tag{18}$$

where, the chroma standard deviation and mean of saturation is indicated as, o_c and φ_l, correspondingly. The weighted coefficients is indicated as, e_1, e_2 and e_3 and luminance contrast is illustrated as, con .

UIQM

The UIQM is the combination of underwater image sharpness measure (UISM), underwater image colorfulness measure (UICM) and underwater image contrast measure (UIConM).

Experimental results

Figure 2 illustrates the experimental outcome of the developed model for underwater image and video enhancement. Figure 2 a) demonstrates the input underwater images, figure 2 b) demonstrates the multi-scale fused images and figure 2 c) signifies the final output image.

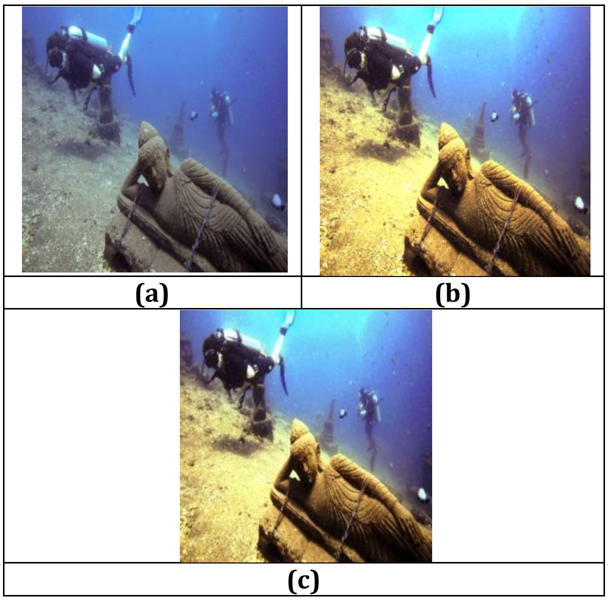
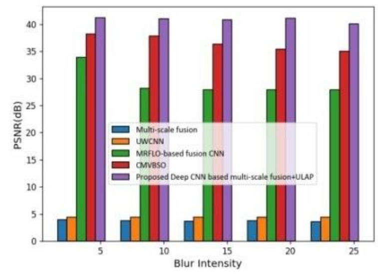


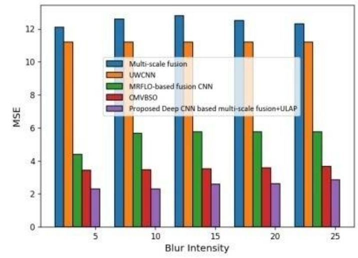
Figure 2. Experimental outcome, a) Input image, b) Multi-scale fused image, c) Final output image

Comparative analysis using Underwater Scene Prior Inspired Deep Underwater Image and Video Enhancement dataset

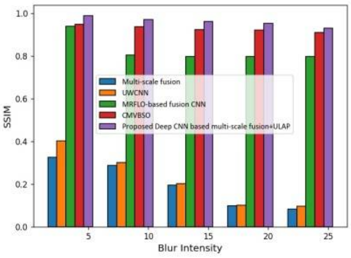
Figure 3 demonstrates the comparative assessment of developed model by changing the blur intensity values based on evaluation metrics. Figure 3 a) illustrates the comparative assessment of developed model based on PSNR. Here, the PSNR values attained by the developed model is 40.05 dB, when the blur intensity is 25 , whereas the existing techniques, such as Multi-scale fusion, UWCNN, MRFLO-based fusion CNN and CMVBSO attained the PSNR values of 3.578 dB, 4.364 dB, 27.88 dB and 35.03 dB, correspondingly when the blur intensity is 25. Figure 3 b) demonstrate the comparative assessment of developed model based on MSE. Here, the developed method attained the MSE values of 2.62 and the existing techniques acquired the MSE of 12.51. 11.17. 5.76 and 3.57, respectively for the blur intensity 20. Figure 3 c) reveal the comparative assessment of the developed model based on SSIM. For the blur intensity 15, then the existing and developed techniques achieved the SSIM values of 0.1956, 0.2023, 0.7979, 0.9228 and 0.9618, correspondingly. Figure 3 d) display the comparative assessment of the developed model based on UCIQE. While considering the blue intensity is 10, then the developed model acquired the UCIQE values of 0.9831, and the existing techniques acquired the UCIQE values of 0.3650, 0.4212, 0.8606 and 0.9556, respectively. Figure 3 e) demonstrates the comparative assessment of the developed model based on UIQM. The developed model acquired the UIQM value of 6.256 for the blur intensity is 5 and the existing techniques acquired the UIQM values of 2.315, 2.961, 5.473 and 5.698, respectively.



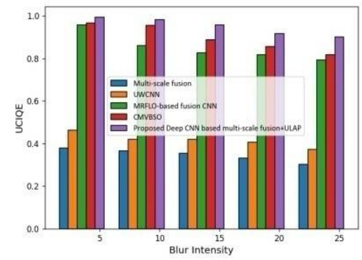
(a)



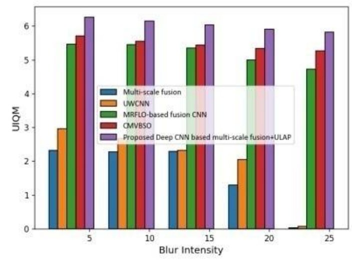
(b)



(c)



(d)

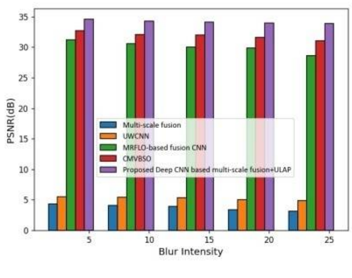


(e)

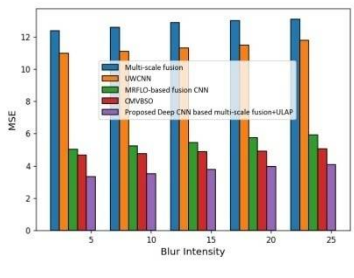
Figure 3 Comparative assessment of developed model based on a) PSNR, b) MSE, c) SSIM, d) UCIQE, e) UIQM

Comparative analysis using an Underwater Image Enhancement Benchmark Dataset and beyond dataset

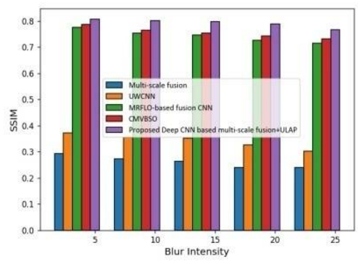
Figure 4 illustrates the comparative assessment of developed model by adjusting the blur intensity values based on evaluation metrics. Figure 4 a) illustrates the comparative assessment of developed model based on PSNR. The existing techniques acquired the PSNR values of 3.973 dB, 5.325 dB, 30 and 31.96 dB for the blur intensity is 15, and the developed method attained the blur intensity of 34.10 dB, correspondingly. Figure 4 b) demonstrates the comparative assessment of developed model based on MSE. For the blur intensity 15, then the existing and developed techniques achieved the MSE values of 12.87, 11.32, 5.442, 4.77 and 3.789, correspondingly. Figure 4 c) reveals the comparative assessment of developed model based on SSIM. When the blur intensity is 10, then the SSIM values acquired by existing approaches are 0.2741, 0.3563, 0.7535 and 0.7645 and the developed method acquired the SSIM values of 0.8010. Figure 4 d) display the comparative assessment of developed model based on UCIQE. The UCIQE values of 0.095, 0.139, 0.341 and 0.428 are achieved by the existing techniques and the UCIQE values of 0.508 is acquired by the developed model for the blur intensity is 20. Figure 4 e) demonstrate the comparative assessment of developed model based on UIQM. Here, the developed method attained the UIQM values of 4.789 and the existing techniques acquired the MSE of 1.022, 1.226, 3.775 and 4.522, respectively for the blur intensity is 25.



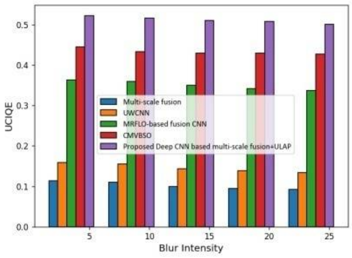
(a)



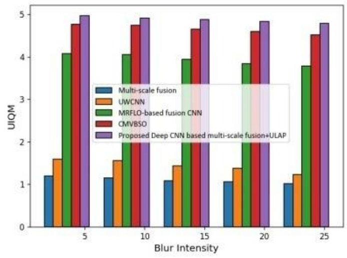
(b)



(c)



(d)



(e)

Figure 4 Comparative assessment based on a) PSNR, b) MSE, c) SSIM, d) UCIQE, e) UIQM

Comparative discussion

Table 1 illustrates the comparative discussion of developed Deep CNN-based multi-scale fusion+ULAP model for underwater image enhancement. From the table 1, it is clearly concluding that the developed Deep CNN-based multi-scale fusion+ULAP model attained maximum PSNR, MSE, SSIM, UCIQE and UIQM values of 40.05, 2.846, 0.931, 0.900 and 5.816, correspondingly using dataset-1. Moreover, the existing techniques attained the PSNR values of 3.578, 4.364, 27.88 and 35.03, MSE values of 12.26, 11.17, 5.761 and 3.684, SSIM values of 0.082, 0.097, 0.797 and 0.911, UCIQE values of 0.302, 0.371, 0.791 and 0.817 and the UIQM values of 0.03, 0.073, 4.727 and 5.266, correspondingly. From the discussion, the developed model attained the optimal performance than the existing techniques due to the effectiveness of developed multi-scale fusion model and ULAP based on Deep CNN. Here, the final fused image is attained by combining two enhanced image based on Deep CNN and ULAP model, thereby the final fused image is attained.

Table 1. Comparative discussion

Dataset	Metrics	Multi-scale fusion	UWCNN	MRFLO-based fusion CNN	CMVBSO	Proposed Deep CNN based multi-scale fusion+ULAP
Dataset-1	PSNR (dB)	3.578	4.364	27.88	35.03	**40.05**
	MSE	12.26	11.17	5.761	3.684	**2.846**
	SSIM	0.082	0.097	0.797	0.911	**0.931**
	UCIQE	0.302	0.371	0.791	0.817	**0.900**
	UIQM	0.03	0.073	4.727	5.266	**5.816**
Dataset-2	PSNR (dB)	3.163	4.866	28.63	31.06	33.93
	MSE	13.05	11.75	5.932	5.065	4.071
	SSIM	0.239	0.302	0.716	0.731	0.766
	UCIQE	0.092	0.134	0.337	0.426	0.501
	UIQM	1.022	1.226	3.775	4.522	4.789

CONCLUSION

In this paper, Deep CNN-based multi-scale fusion+ULAP technique is developed for multi-scale image fusion. Here, the multi-scale fusion process is carried out to fuse the normalized weight of white balanced image and gamma corrected images. The blur detection and estimation is carried out using Laplacian's variance, which reduces the distortions in the image and the depth estimation is done by the optimized ULAP model. In addition, the deblurring of image is carried out by the adaptive feature fusion CNN and the pixel enhancement is done by the statistical model, namely T2FCS filter, which improves the quality of image. At last, the final fusion process is carried out by combining output of multi-scale fusion and output of optimized ULAP-based enhancement. In addition, the experimental result demonstrates that the developed method outperformed various existing techniques and attained the higher PSNR of 40.05 dB, lower MSE of 2.846, higher SSIM of 0.931, higher UCIQE of 0.900, and higher UIQM of 5.816, respectively. In future, the performance of developed enhancement model can be enhanced by applying various effective optimized deep learning techniques.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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