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Underwater Image Enhancement with Optimal Histogram using Hybridized Particle Swarm and Dragonfly

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Underwater Image Enhancement with Optimal Histogram using Hybridized Particle Swarm and Dragonfly

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Abstract: Typically, the underwater image processing mainly concerned on balancing the color change distortion or light scattering. Various researches have been processed under these issues. These research approaches often argue for the increment of visibility and scene contrast enhancement, though the distortion that produced by the difference in wavelength attenuation is still remained intact. Also, these approaches remains ineffective in image blurriness removal that produced due to light scattering. A systematic approach is necessary for solving all these possible errors and this research work thus aims to introduce a new underwater image enhancement approach that enhances the quality of the underwater image. This proposed model incorporates two phases namely contrast correction and color correction. Moreover, two processes are involved within the contrast correction model namely (i) Global contrast correction and (ii) Local contrast correction. For the image enhancement, the main target is on the histogram evaluation, and therefore the optimal selection of histogram limit is very essential. For this optimization purpose, a new hybrid algorithm is introduced namely Swarm updated Dragonfly Algorithm (SU-DA), which is the hybridization of Particle Swarm Optimization (PSO) and Dragonfly Algorithm (DA). Further, this paper mainly focused on Integrated Global and Local Contrast Correction (IGLCC). The

proposed model is finally distinguished over the other conventional models like CLAH, IGLCC, dynamic stretching IGLCC-Genetic Algorithm (IGLCC-GA), IGLCC- Particle Swarm Optimization (IGLCC-PSO), IGLCC- Firefly (IGLCC-FF) and IGLCC- Cuckoo Search (IGLCC-CS), ICLCC-DOCS (IGLCC-Distance Oriented Cuckoo Search) and DA, and the superiority of proposed work is proved.

Keywords: Underwater Image; Color Correction; Contrast Correction; Optimization; Dragonfly Algorithm.

Nomenclature

Abbreviation	Description
WT	wavelet transform
HE	histogram equalization
CLAHE	contrast limited adaptive histogram equalization
CLAHE-WT	contrast limited adaptive histogram equalization and wavelet transform
PSNR	peak signal to noise ratio
MSE	mean square error
EMD	Empirical Mode Decomposition
IMF	Intrinsic Mode Function
GA	Genetic algorithm
RGB	Red Green and Blue
HSI	hue–saturation–intensity
WDF	wavelet-domain filtering
CHS	constrained histogram stretching
PDE	partial differential equation
DWT	Discrete Wavelet Transform
WCID	wavelength compensation and image dehazing
CLAHS	contrast limited adaptive histogram specification
PDF	probability distribution function
CDF	cumulative distribution function

1. Introduction

UNDERWATER image processing [9] [10] [11] is considered as a promising one because of the underwater environment’s physical properties. In most of the cases, the absorption and scattering process degrades the captured underwater images. The camera that received the light in the underwater scenario has been majorly produced using three main components namely, forward scattering [15] [16] component that arbitrarily diverges the light on its paths to the camera; a straight component that replicates light from the objects; and a back scattering component that diverges light along the camera, once previous to the light truly achieves the objects. A linear superposition can refer the underwater image using these aforesaid three components. The image blurring is caused by the forward scattering component, while the scenario details are masked by the back scattering [17] [18] component. Furthermore, the unwanted noise and the effect of scattering can be increased by the marine snow, which is the macroscopic particle that floats on the marine. Some challenges are there in the degraded underwater images while using that for extracting valuable information and display function to carry on processing, like aquatic robot inspection, marine biology and archaeology, and marine ecological research. Hence, the underwater image enhancement for both display and analysis needs further effective models.

The area of underwater image processing [12] [13] [14] has achieved a major concern over many researchers for the past numerous decades. Few of the present models are summarized in detail on the underwater environmental development and classified the models on the basis of image enhancement [19] [20] and image restoration. The models on image restoration are on the basis of the scattering model for improving the visibility, dehazing, the energy attenuation method and restore color of the underwater image. Though, these models that explained are depended on the earlier knowledge of the circumstance, like optical length, temperature, scene depth, conductivity, illumination, and spatial location. The vision system can be matched by deploying more sensors. Moreover, when compared to the image enhancement method, the processing tome of this method was extremely larger. Further, on comparing with the image restoration approach [21] [22], the image enhancement approaches are generally quicker and simple. Many researches has been evolved and reported for enhancing the contrast and to eliminate the noise in the underwater image. Some of the broadly used methods are WT [23], HE [24] and CLAHE [25]. Though, all these models need further improvement for enhancing the underwater image quality. The contribution of this research work is as follows:

- This paper mainly intends to propose a new underwater image enhancement approach that involves two stages namely, contrast correction, and color correction.
- Further, the contrast correction model incorporates two processes like Global contrast correction and local contrast correction.
- Moreover, the optimal selection of the histogram limit is made by deploying a new optimization concept.
- For this purpose, a new hybrid algorithm is introduced, which is termed as SU-DA, which is the combination of PSO and DA.
- To the end, the proposed model regarding the performance is analyzed over the other conventional models in terms of some measures.

This paper is arranged in this following format: Section II depicts the literature study on enhancement over the underwater image quality. Section III delineates the underwater image enhancement model with optimized histogram limits. Section IV expresses the optimized histogram limits by new Swarm updated Dragonfly Algorithm. Results and their discussions are explained in Section V. Section VI ends the paper.

2. Literature Survey

2.1 Related Works

In 2017, Qiao *et al.* [1] have presented a narrative model on the basis of CLAHE-WT for improving the image quality of sea cucumber. On the basis of Rayleigh distribution, the

CLAHE has been deployed for processing the increasing contrast of underwater image. On the basis of soft threshold, the de-noising was made by WT. the analysis on qualitative result has demonstrated that the adopted model has betterment in quality improvement and in maintaining the image details. The quantitative analysis has been made using 120 underwater image samples and the outcome was verified in terms of PSNR, entropy, and MSE. From this analysis, the visual quality of sea cucumber underwater gray image was enhanced by this proposed model.

In 2015, Zhao *et al.* [2] have formulated the quality and colors of images were bad in the underwater condition because of the light's particular propagation properties in water, and there was a relation among the degradation effect and water's optical properties. The water medium's inherent optical properties have a correlation with the background underwater image color. This framework has implemented the model to operate the water's inherent optical properties on the basis of underwater image formation method from the background color of underwater images. The experimental result has revealed that the implanted model has been a better model for underwater image enhancement by efficiently estimating the inherent optical properties.

In 2012, Celebi and Erturk [3] have introduced an underwater image enhancement algorithm on the basis of EMD. Here, at first, the EMD has decomposed every spectral underwater image components as IMFs. For attaining the enhanced image with maximized visual quality, the construction of enhanced image has been made by merging the spectral channel's IMF with diverse weights. The GA was employed for processing the weight estimation, where, the IMF weights were computed in order to optimize the average gradient and entropy sum of reconstructed image. From the result, it has proved that the implanted model has offered better solutions than other existed models.

In 2017, Vasamsetti *et al.* [4] have evolved to apply a set of energy functional on the detailed coefficients and approximation of the image. The image' average intensity value was adjusted by making a modification in approximation coefficients of RGB components, followed by these coefficient's color correction at advanced scales. The image local contrast has been enhanced by using the detailed coefficient processing. Qualitative and Quantitative analysis on the performance of the implemented model has been evolved under three underwater datasets having various depths. The hue histogram of input and output images were compared using the Qualitative Analysis. The proposed model outcomes have been distinguished from other models and thus explains the significance removal of color cast as well as prevents the detailed structural characteristics.

In 2016, Li *et al.* [5] have evolved the methodical underwater image enhancement algorithm, where the contrast enhancement algorithm and the underwater image dehazing algorithm were incorporated. Further, an efficient underwater image dehazing model has been implemented based on the minimum information loss principle for retrieving the natural appearance, color, and visibility of underwater images. The underwater image's brightness and contrast have been improved by introducing a new effective contrast enhancement method on the basis of type of histogram distribution prior. Two versions of improved outcome have been yielded from this implemented model. The version that has comparatively natural appearance and genuine color has been selected appropriately for display. The other one was utilized to extract the more necessary information and presenting additional details. The performance of the implemented model has been evaluated using the simulation investigation on color accuracy, application tests comparison both qualitatively and quantitatively. The result has shown the better attainment of more precise color restoration, visual quality, and more valuable information.

In 2012, Chiang and Chen [6] have implanted a narrative systematic model for improving the underwater image using dehazing method, in order to acquire the influence of artificial light source possible presence into account and for compensating the attenuation discrepancy towards the propagation path. The segmentation of foreground and background within a scene was made once after the depth map was estimated. At the time of image capturing process, the artificial light source employment has been determined by comparing the light intensities of background and foreground. After the artificial light effect compensation, the correction of discrepancy and haze phenomenon along the propagation path of underwater in wavelength attenuation was handled. In accordance to the residual energy ratios of diverse color channels that existed in background light, the water depth within the image scene has been evaluated. Color changing compensation has been conducted on the basis of the quantity of attenuation regarding every light wavelength, in order to retrieve the color balance. The evaluation was performed in both objective and subjective methods and the results have confirmed that the proposed WCID has a precise improvement in visibility and better color fidelity.

In 2018, Hou *et al.* [7] have developed a new technique for underwater color image enhancement by merging the HSV color models and HSI. Here, in the HIS and HSV color models, the implemented WDF and CHS algorithms were operated, correspondingly. Initially, converts the degraded image from the RGB color model to HIS color model, while the preservation of hue component H was made and the S and I components have executed with WDF algorithm. In similar, further conversion of this image was made into HSV color model, which has invariant H component and the S and V components were applied with CHS algorithm. The main contribution of this work was about the H preservation model, which enhances the quality of image regarding the non-uniform illumination, contrast, denoising, and colour rendition.

In 2017, Nnolim [8] has explained about the enhanced PDE - based formulations for the enhancement of underwater image for merged local and global contrast operators. The challenges on traditional closed-form techniques and the issue on optimal stopping time of previous PDE-based techniques have been eliminated by this algorithm. The optimization of multiple image metrics directs the fundamental characteristics that comprised of enhanced simultaneous combination, control and augmentation of several individual global and local processes. The optimal algorithm operation was making sure regarding the arithmetical and visual results and the implemented model has possessed fully and quicker automated processing of several images. The comparative execution has stated that the enhanced implemented method has yielded superior outcomes than any other conventional models.

Table 1: Features and Challenges of Conventional Underwater Image Enhancement approaches

Author [citation]	Methodology	Features	Challenges
Qiao *et al.* [1]	CLAHE-WT	❖ Significant improvement in contrast ❖ Reduced noise	❖ Needs further processing on image
Zhao *et al.* [2]	Inherent optical derive model	❖ Convenient and effective ❖ Corrects colors ❖ Eliminates the degraded underwater images with better effect	❖ Needs artificial light source ❖ Needs solution on radiation in future
Celebi and Erturk [3]	EMD	❖ Provides better clarity and color ❖ Image contrast is improved	❖ Result may be meaningful ❖ Make no assumption on stationary of signal
Vasamsetti *et al.* [4]	DWT	❖ Color and contrast are enhanced ❖ Effectively removes the color cast of the image	❖ Difficult to understand ❖ Critical to interpret the results
Li *et al.* [5]	Underwater image	❖ Minimize the information loss	❖ Only the distance between the camera

	enhancement model	❖ Increased contrast and brightness ❖ Improved visibility	and the objects are considered ❖ Needs reduction in the noise effect
Chiang and Chen [6]	WCID	❖ Restore image color balance ❖ Better haze removing	❖ Accurate measurement of Light energy loss is difficult ❖ Error may affect the precision and underwater propagation distance
Hou *et al.* [7]	Hue preserving-based approach	❖ Solves non-uniform illumination ❖ Successful color rendition	❖ Needs improvement over algorithm performance ❖ Needs focus on quantitative metrics
Nnolim [8]	PDE	❖ Improves color correction, edge and contrast enhancement ❖ Eliminates noise enhancement and over exposure	❖ An exact analytic solution is not available ❖ Numerical methods are necessary

2.2 Review

The feature and challenges of the conventional underwater image enhancement approaches are stated in Table 1. Various other methods are evolved to enhance the underwater image quality that gets affected by poor lighting, external factors and so on. CLAHE-WT [1] poses significant improvement in contrast and has reduced noise. However, needs further processing on image, which is the main drawback of this method. Inherent optical derive model [2] is convenient and effective, corrects colors and eliminates the degraded underwater images with better effect. Though lacks in artificial light source and needs solution on radiation in future. EMD [3] provides better clarity and color and the image contrast is improved. But, the result may be meaningful and does not make assumption on stationary of signal. DWT [4] has enhanced color and contrast as well as effectively removes the color cast of the image. Yet it is difficult to understand and critical to interpreting the results. Underwater image enhancement model [5] minimizes the information loss, increased contrast and brightness, and improved visibility. The main challenges are: only the distance among the camera and the objects are considered and needs a reduction in the noise effect. WCID [6] restores the image color balance and has better haze removing. However, accurate measurement of Light energy loss is difficult and error may affect the precision and underwater propagation distance. Hue preserving-based approach [7] solves non-uniform illumination and has successful color rendition. However, needs improvement over algorithm performance and needs to focus on quantitative metrics. PDE [8] improves color correction, edge and contrast enhancement and eliminates the noise enhancement and over exposure. Exact analytic solution is not available and numerical methods are necessary. This is the main drawback that existed in this methodology.

3.Underwater Image Enhancement Model With Optimized Histogram Limits

3.1 Proposed System Model

Fig. 1 depicts the implemented underwater image enhancement model. The following is the brief explanation on this process: consider the input image as In that is processed in channel decomposition. The attained output image is then provided to the contrast correction phase, which comprised of two stages namely, global and local contrast correction. On considering the global contrast correction phase, the initial processing of the image is made for estimating the maximum, minimum and midpoint of image histogram. On the basis of midpoint values, this processed image is sub-categorized as two parts. Subsequent to this, the stretching of image is made in the direction of upper and lower regions. The outcome image is then forwarded to local contrast correction, which operates by deploying the CLAHS model [33]. After the contrast correction, the outcome image can be expressed as In_A. This image is then subjected to color correction process, which converts the RGB image into HSV color model. In the midpoint region, this image is split as S and V components and the starching of these components is made regarding the Rayleigh distribution that lies in the range of 1%. To the end, the channel composition is performed within the color correction module and the outcome image is then changed from HSV to RGB. On the whole, the outcome image that attained is defined as In_G.

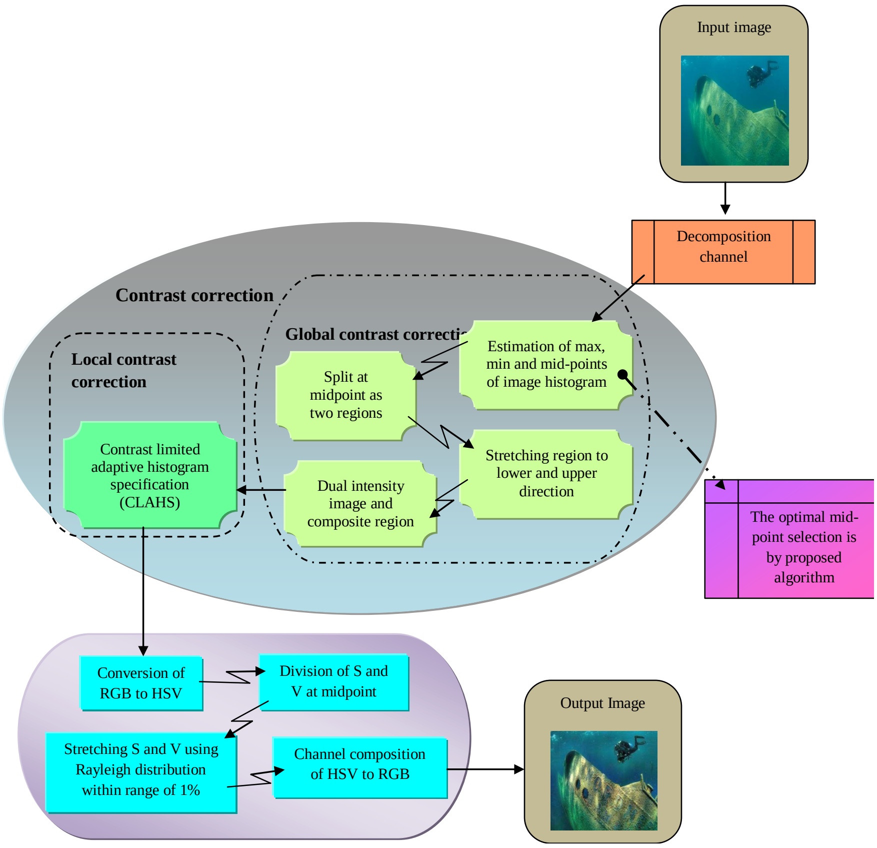


Fig. 1. Art of Proposed underwater image enhancement method

3.2 Contrast correction

Global contrast correction: Firstly, the processing of the image is made on the basis of evaluating the image histogram's minimum, maximum and midpoint values. The image can be scattered with green blue and red. The lowest or minimum intensity and the highest or maximum intensity are defined by $I_{\min}$ and $I_{\max}$, respectively. The value of midpoint I_{mid} evaluation is made as per the Eq. (1).

$$I_{mid} = \frac{I_{\min} + I_{\max}}{2} \tag{1}$$

The histogram division is performed after the midpoint value estimation. Further, the image histogram is categorized into two regions namely lower and upper region. Every region's stretching process is defined by the following.

(i)Lower section is stretched or extended above maximum intensity level along least output value $f_{\min}$ of 5%.

(ii)Upper section is stretched or extended above minimum intensity level along the maximum output value $f_{\max}$ of 5%.

Eq. (2) explains the stretching process, where the input and output pixels are denoted by X_{in} and X_{in}. $I_{\min}, I_{\max}, f_{\min}$ and $f_{\max}$ delineates the least and highest level of intensity for both the input and output images, in that order.

$$Y_{out} = (Y_{in} - I_{\min})\left(\frac{f_{\max} - f_{\min}}{I_{\max} - I_{\min}}\right) + f_{\min} \tag{2}$$

Moreover, the processing of region composition and dual intensity images are carried out. The lower stretched images and upper stretched images produce new two images. Altogether, these images are defined as dual-intensity image and the integration is made by means of average values. The integration of images are made depends on the particular image channels and then two distinct image channels are plotted with each other. After that, the estimation of average values between these channels is performed.

Local Contrast Correction: The CLAHS process is employed within this stage and the process is explained as follows: (a) Image is categorized as tiles (b) Clip limit application (c) Histogram performance specification based on Rayleigh distribution and (d) Image tiles composition. There is a restriction of 2x2 regions in the division of image tiles. This has been made for limiting the uncontrolled contrast correction. The evaluation processing consumption is minimized by using a few counts of tiles.

Consequently, the implementation of clip limit is made for protecting the image's over-contrasting effect. To a definite extent at specific intensity level, the count of pixel is restricted and the remaining pixels with exceed limits can get eliminated. The dispersing of additional pixels is made to the whole intensity levels, by which the pixel's count can be maximized within the whole intensity level. This iteration process will repeat until the added pixels are appropriately smaller to be ignored.

The intensity level in the image histogram is mapped using the Rayleigh distribution after the implementation of the clip limit. Eq. (3) and (4) portrays the Rayleigh distribution's PDF and CDF. In this, ip denotes the input pixel and in Rayleigh distribution, the distribution function is denoted as α .

$$PDF_{Rayleigh} = \frac{ip}{\alpha^2} e^{\left(-ip^2 / 2\alpha^2\right)} \tag{3}$$

$$CDF_{Rayleigh} = 1 - e^{\left(-ip^2 / 2\alpha^2\right)} \tag{4}$$

3.3 Color correction

Here, at first, the outcome image In_A obtained from contrast correction model image is converted into HSV color models. The image color can get changed notably by the effect of S and V color model. Therefore, this is defined as an important component for maximizing the image clarity and visibility.

Once the conversion is completed, the S and V components are divided in the midpoint region. The Rayleigh distribution having a range of 1% is deployed for the stretching of S and V parameters by using the highest and lowest intensity levels. The attainment of maximum and minimum points of parameters is restricted by assigning the limit, which avoids the under-saturation and oversaturation having under-brightness and over-brightness. The evaluation of midpoint is already defined in Eq. (1).

The subsequent step is the process of stretching the S and V components based on their midpoints, and is given as follows:

(i) The input value within lower level is achieved from $I_{\min}$ to I_{mid}. The input value is stretched to the output histogram regarding the novel dynamic range of [1% 99%].

(ii) The input value within upper level is accomplished from I_{mid} to $I_{\max}$. The value of the input is stretched to the output histogram regarding the narrative dynamic range of [1% 99%]

The formula on Rayleigh stretched is given in the following:

$$\begin{aligned} &Rayleigh \\ &streched = \frac{\left[(Y_{in} - I_{\min})\left(f_{\max} - f_{\min} \middle/ I_{\max} - I_{\min}\right) + f_{\min}\right]}{\alpha^2} \\ &\quad .\exp \frac{-\left[(Y_{in} - I_{\min}\left(f_{\max} - f_{\min} / I_{\max} - I_{\min}\right) + f_{\min}\right]^2}{2\alpha^2} \\ &\quad = \frac{Y_{in} f_{\max} - Z_{in} f_{\min} - I_{\min} f_{\max} - f_{\min} I_{\max}}{\alpha^2 (t_{\max} - t_{\min})} \\ &\quad .\exp \frac{-[Y_{in} f_{\max} - Y_{in} f_{\min} - I_{\min} f_{\max} - f_{\min} I_{\max}]^2}{2\alpha^2 (t_{\max} - t_{\min})^2} \end{aligned} \tag{5}$$

The $I_{\max}$ value is substituted by I_{mid} within the level of lower-stretched. Same as in the level of upper-stretched, the $I_{\min}$ value is substituted by I_{mid}.

To the end, the implementation of component composition model is carried out after the completion of the stretching process. The S parameter's lower-stretched and upper-stretched histogram is incorporated by using the average value H_{avg}, and that is stated in Eq. (6). In this, the intensity value at locations (u,v) having the lower-stretched and upper-stretched histograms is denoted by $H_{LW}(u,v)$ and $H_{UP}(u,v)$, correspondingly. The V parameters also processed with this same integration process. A HSV color mod4el image can be generated by combining these entire H, S and V components before changing them into RGB color model.

$$H_{avg} = \frac{H_{LW}(u,v) + H_{UP}(u,v)}{2} \tag{6}$$

4. Optimized Histogram Limits By New Swarm Updated Dragonfly Algorithm

4.1 Solution Encoding

In this, the enhancement of the underwater image is mainly on the basis of the evaluation of image histogram. Hence, in order to attain the accurate enhancement in the image quality, the limits (lm) (mid-point) have to be optimal. For this optimal selection of limits lm, a new proposed algorithm SU-DA is introduced in this framework. The solution that is given as the input to the proposed model is defined in Fig. 2. In this, the minimum and maximum limits of the low-level histogram is depicted as $Low_{\min}$ and $Low_{\max}$, while the minimum and maximum limits of high-level histogram are delineated as $High_{\min}$ and $High_{\max}$, respectively. Eq. (7) provides the condition on optimal limit.

$$\begin{aligned} lm_{\min}^{low} &< lm_{\max}^{low} \\ lm_{\min}^{high} &< lm_{\max}^{high} \end{aligned} \tag{7}$$

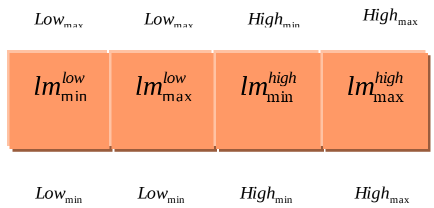


Fig. 2. Solution Encoding of Implemented model

4.2 Objective Function

The implemented model main objective is stated as per the Eq. (8), in this ft_1, ft_2 and ft_3 was explained using Eq. (9), (10) and (11), correspondingly.

$$Obj = \min(w_1 \times ft_1 + w_2 \times ft_2 + w_3 \times ft_3) \tag{8}$$

$$ft_1 = brisque(outimage) \tag{9}$$

$$ft_2 = JNBM\_compute(outimage) \tag{10}$$

$$ft_3 = Fade(outimage) \tag{11}$$

4.3 Conventional PSO

PSO [26] is termed as the population-based algorithm, which is truly designed to stimulate the social behavior of bird flocks. However, it is then simplified for performing optimization, where every individual is taken as particles. This PSO algorithm firstly leaves the particles in arbitrary position that are moved randomly in definite directions within the search space. The particle direction is altered linearly, hence it moved towards the best previous position of itself and its peers. Later, on considering some fitness measure, it searched for its vicinity and confidently identifies the superior positions $f : \Re^{no} \to \Re$.

The position of the particle is termed as $\vec{y} \in \Re^{no}$, and the velocity is $\vec{v}$. Regarding the two formulas, both these parameters are selected first in random and updated iteratively. The update formula for velocity of the particle is stated as per the Eq. (12).

$$\vec{v} = \tau\vec{v} + \phi_e s_e(\vec{e} - \vec{y}) + \phi_h s_h(\vec{h} - \vec{y}) \tag{12}$$

In this, the inertia weight is defined as the user-defined behavioral parameter $\tau \in \Re$, and the recurrence quantity in particle's velocity can be controlled. The earlier best position of particle is $\vec{e}$ and the earlier best position of swarm by which the communication of particles is handled implicit to each other is given as $\vec{h}$. The user-defined behavioral parameters $\phi_e, \phi_h \in \Re$ and the stochastic variables $s_e, s_h \sim U(0,1)$ are used for weighting these functions. The particles can move towards other search space positions, owing to the velocity added with the current particle position with its fitness improvement, and that is given in Eq. (13).

$$\vec{y} = \vec{y} + \vec{v} \tag{13}$$

The challenges on distance that a particle can travel in the single step have to be imposed, addition to the enforce search-space boundaries behind the particle's position update. For this purpose, the particle velocity $\vec{v}$ is bounded to the full search space's dynamic range. Hence, by one step, the particles might be moved from one to other search space boundary.

The PSO model is simplified by taking the mathematical description parts that need to be eliminated by the algorithm. The update velocity formula in Eq. (1) is defined as the user-defined behavioral parameter's weighted sum and numerous vectors related to the swarm's state and its individual particles. The communication among the particles can be banned by eliminating the part that contains the best-known position of swarm $\vec{h}$ by assigning $\phi_h = 0$. The straight recurrence in Eq. (1) can be eliminated by assigning the inertia weight τ to zero, which in turns source the particle with no diligence in its following path.

Regardless, the testing of the simplification in this comprised of neglecting the utilization of own previous best-known position of particle $\vec{e}$ by assigning $\phi_e = 0$. Hence the Eq. (12) is changed as per the Eq. (14).

$$\vec{v} = \tau\vec{v} + \phi_h s_h (\vec{h} - \vec{y}) \tag{14}$$

4.4 Conventional DA

The lifecycle of dragonfly is comprised of two stages namely, nymph and adult and total of 3000 diverse species exist in this species. They survived as nymph for most of their lifetimes, and become adults by undergoes metamorphism. This DA [27] algorithm is introduced based on the inspiration of static and dynamic swarming behaviors. The following two phases namely exploitation and exploration are very much similar to these swarming behavior. In exploration or static swarm, small clusters are made by the Dragonflies and flutters within a small area for hunting the preys. The main features of this static swarm are the local movements and rapid alteration in the flying path. In exploration or dynamic swarms, the dragonflies with enormous quantity formulate the swarms to migrate over long distance in one direction. The survival of the swarm is their main objectives: hence, the entire swarm individual's gets attracted over the food sources and diverted by the explicit enemies. On account of the two behaviors, the swarm's individual position update consists of five main factors. The parameters are defined as alignment, attraction (along food sources), control cohesion, distraction (along outward enemies) and separation of swarm individuals. Eq. (15) computes the neighbor $C_{\hat{i}}$, separation of $\hat{i}^{th}$ dragonfly.

$$C_{\hat{i}} = -\sum_{\hat{j}=1}^{N'} (Z' - Z'_{\hat{j}}) \tag{15}$$

In Eq. (15), the present individual position is given by Z', $\hat{j}^{th}$ neighbouring individual position is expressed as $Z'_{\hat{j}}$ and the count of neighboring individuals is denoted as N'. Eq. (16) provides the calculation of alignment.

$$Al_{\hat{i}} = \frac{\sum_{\hat{j}=1}^{N'} V'_{\hat{j}}}{N'} \tag{16}$$

In this, the velocity of $\hat{j}^{th}$ the neighbouring individual is indicated as $V'_{\hat{j}}$. The estimation on cohesion is given by Eq. (17). The calculation of attraction over the food source is given as per the Eq. (18). In this, the food source position is given by Fd. Eq. (19) depicts the calculation on distraction over enemies.

$$Co_{\hat{i}} = \frac{\sum_{\hat{j}=1}^{N'} Z'_{\hat{j}}}{N'} - Z' \tag{17}$$

$$At_{\hat{i}} = Fd - Z' \tag{18}$$

$$D_{\hat{i}} = Ene - Z' \tag{19}$$

Here, the enemy position is assigned as Ene. The dragonfly’s behavior is based on the merging of five corrective patterns. In this, two vectors are assumed for updating the dragonflies’ position within a search space and for simulating the movements: position (Z') and step ($\Delta Z'$). The step vector and velocity vector in PSO are the analogous one, and on the basis of PSO algorithm framework, the DA algorithm has been evolved. Eq. (20) explains the step vector, which demonstrates the direction of dragonflies’ movement.

$$\Delta Z'_{t+1} = (c'C_{\hat{i}} + al'Al_{\hat{i}} + co'Co_{\hat{i}} + at'At_{\hat{i}} + d'D_{\hat{i}}) + \delta.\Delta Z'_t \tag{20}$$

In this, the separation weight is given by c', the $\hat{i}^{th}$ individual separation is denoted as $C_{\hat{i}}$, alignment weight is expressed as al', the alignment of $\hat{i}^{th}$ individual is depicted as $Al_{\hat{i}}$, cohesion weight is co', the $\hat{i}^{th}$ individual cohesion is $Co_{\hat{i}}$, food factor is at', the food source of $\hat{i}^{th}$ individual is delineated as $At_{\hat{i}}$, enemy factor is denoted by d', the $\hat{i}^{th}$ individual enemy position is given by $D_{\hat{i}}$, inertia weight is defined with δ and iteration count is given as t. At the time of optimization using the aforesaid equation factors, the achievement of diverse exploitative and explorative behaviors is made. Eq. (21) provides the position vector calculation.

$$Z'_{t+1} = Z'_t + \Delta Z'_{t+1} \tag{21}$$

where t denotes the present iteration. For exploring the search space, the dragonflies having low cohesion weights and high alignment was assigned, whereas for exploiting the search space, the high cohesion and low alignment dragonflies were assigned. The dragonflies have to roam around the search space when there has no neighboring solution by means of random walk (Levy flight), in order to improve the randomness, and the exploration and stochastic behavior. For this, the update position of dragonflies is made as per the Eq. (22), (23) and (24).

$$Z'_{t+1} = Z'_t + Levy(l) \times Z'_t \tag{22}$$

$$Levy(l) = 0.01 \times \frac{ra_1 \times \Phi}{|ra_2|^{1/l}} \tag{23}$$

$$\Phi = \left(\frac{\Gamma(1 + \xi \times \sin\left(\frac{\pi\xi}{2}\right)}{\Gamma\left(\frac{1+\xi}{2}\right) \times \xi \times 2^{\left(\frac{\xi-1}{2}\right)}} \right)^{1/\xi} \tag{24}$$

$$\Gamma(z) = (z-1)! \tag{25}$$

In this, the dimension of position vector is given by l, the two random numbers that lie in the interval 0 and 1 is given by ra_1 and ra_2, and ξ is assigned as a constant. The steps and position of every dragonfly in every iteration is updated as per the Eq. (9)-(11). The determination of each neighbor of every dragonfly is must by computing the Euclidean distance among the entire dragonflies and chooses N' of them, in order to update Z' and $\Delta Z'$ vector. This update process on position continues repeatedly until it satisfies the final criteria. Algorithm 1 depicts the conventional pseudo code of DA algorithm.

Algorithm 1: Pseudo code of conventional DA algorithm	
Initialize the population of dragonflies $Z_i'(i=1,2,....,n)$	
Initiate the step vectors $\Delta Z_i'(i=1,2,....,n)$	
while the end criteria are not fulfilled	
Estimate the entire dragonflies' objective values	
Update the enemy and food source	
Update $\delta, c, al, co, at\ and\ d$	
Estimate $C, Al, Co, At\ and\ D$ as per the Eq. (15) to (19)	
Update neighboring radius	
if a dragonfly pose minimum one neighbor dragonfly	
	Update the velocity vector and position vector using the Eq. (20) and (21) respectively
else	
	Update position vector as per the Eq. (22)
endif	
Verify and correct the new position on the basis of variable boundaries	
End while	

4.5 Proposed Algorithm

The PSO algorithm has many advantages like simple implementation, robust, and is efficient on resolving the complex problems. Even though, some demerits are there that needs to pose in the latter future. Some of them are easier on falling into local optimum within the high-dimensional space and on the iterative process, lower convergence rate and so on. Similarly, the DA algorithm is the one that developed based on the inspiration by dragonflies behavior. This is considered as a new metaheuristic optimization algorithm to solve the discrete, single and multi-objective problems. However, this algorithm further needs improvement or enhancement on problem-solving. Hence, this paper has made an attempt to introduce a new hybrid algorithm for enhancing the underwater image quality namely, SU-DA, which is the hybrid form of PSO and DA.

The proposed algorithm is stated as follows: in the conventional DA algorithm, after updating the neighboring radius, it checks for the condition. If the dragonfly has minimum one neighboring dragonfly, then the velocity vector and position vector gets updated as per the Eq. (9) and (10), respectively. In the proposed algorithm, under the same condition, the dragonfly position update is replaced by incorporating the PSO update that is given in Eq. (1). The Pseudo code of the proposed SU-DA algorithm is stated in Algorithm 2. The flowchart of the Proposed SU-DA algorithm is stated in Fig. 3.

Algorithm 2: Pseudo code of Proposed SU-DA algorithm	
Initialize the population of dragonflies $Z_i'(i=1,2,....,n)$	
Initiate the step vectors $\Delta Z_i'(i=1,2,....,n)$	
while the end criteria is not fulfilled	
Estimate the entire dragonflies' objective values	
Update the enemy and food source	
Update $\delta, c, al, co, at\ and\ d$	
Estimate $C, Al, Co, At\ and\ D$ as per the Eq. (15) to (19)	
Update neighboring radius	
if a dragonfly pose minimum one neighbor dragonfly	
	Updating the position as per the PSO update equation is given in Eq. (12)
else	
	Update position vector as per the Eq. (22)
endif	
Verify and correct the new position on the basis of variable boundaries	
End while	

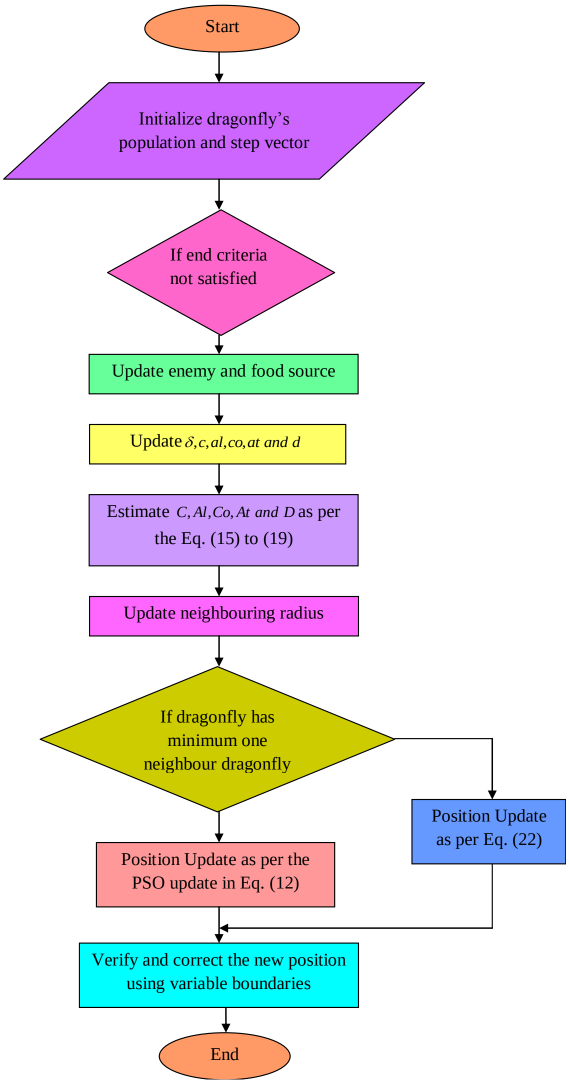


Fig. 3. Flowchart representation of Proposed SU-DA Algorithm

5. Results And Discussions

5.1 Simulation Setup

The simulation of this proposed underwater image enhancement model was made in MATLAB 2018a. The datasets that are used in this are downloaded from Dataset-1: http://www.whoi.edu/science/AOPE/singhdatasets/stellwagen_bank.zip, Dataset-2: http://www.whoi.edu/science/AOPE/singhdatasets/bolder_imagery.zip, Dataset-3: https://in.mathworks.com/matlabcentral/fileexchange/ 51082-underwater-images. Further, the analysis has been made under the three performance measures like Brisque, Jnbm, and Fade, and moreover, the statistical analysis was also made. The performance of the implemented model has been distinguished over the other models like CLAHS [33], dynamic stretching [32], IGLCC [31], IGLCC-GA [28], IGLCC-PSO [26], IGLCC-FF [29], IGLCC-CS [30], IGLCC-DOCS [34] and DA [27] regarding the aforesaid measures. The analysis results on the image of proposed SU-DA under datasets 1, 2 and 3 over the conventional models are symbolized in Fig. 4–6 respectively.

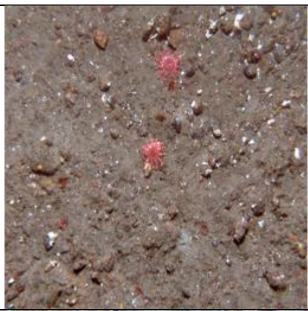
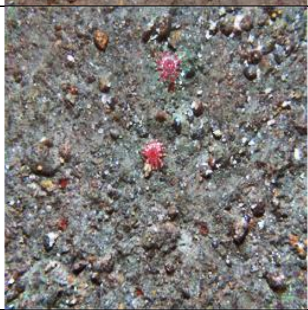
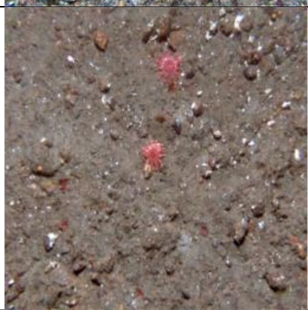
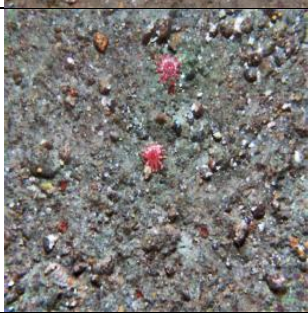
Original image		
Image result of CLAH		
Image result of Dynamic Stretching		
Image result of IGLCC		

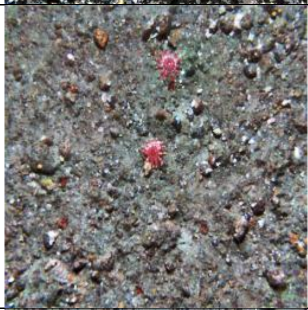
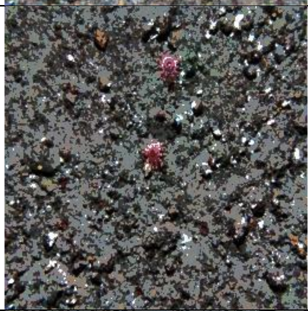
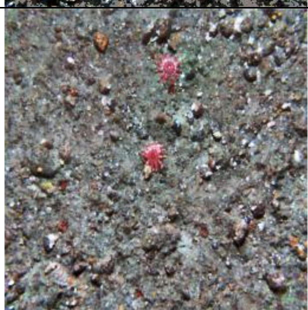
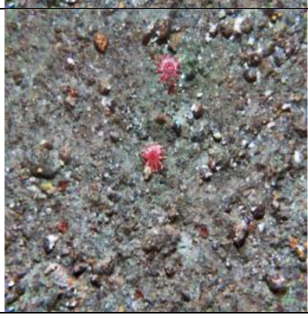
Image result of IGLCC_GA		
Image result of IGLCC_PSO		
Image result of IGLCC_FF		
Image result of IGLCC_CS		
Image result of IGLCC_DOCS		
Image result of IGLCC_DA		

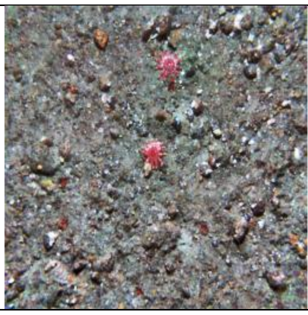
Image result of SU-DA		

Fig. 4. Image results on dataset 1 of Proposed and Conventional models (a) Image 1 and (b) Image 2

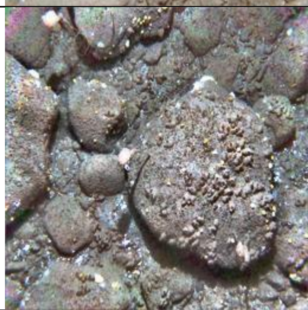
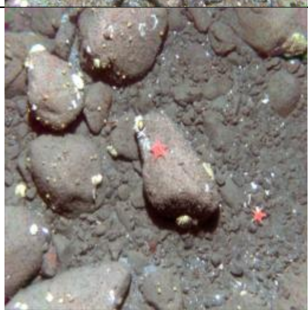
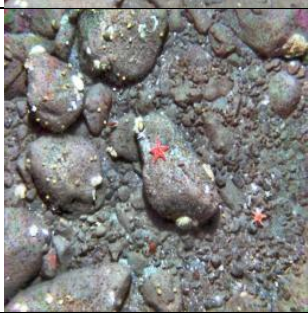
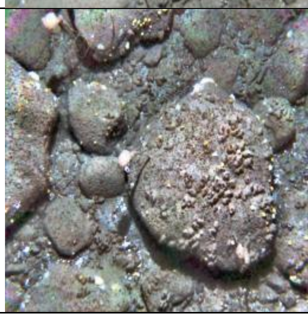
Original image		
Image result of CLAH		
Image result of Dynamic Stretching		
Image result of IGLCC		

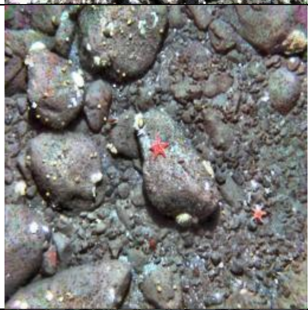
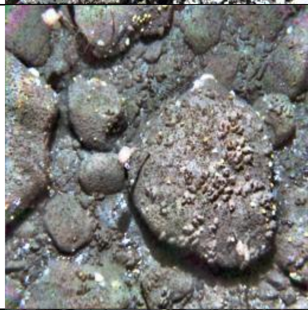
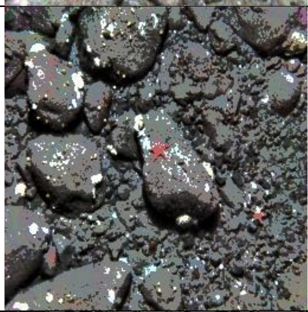
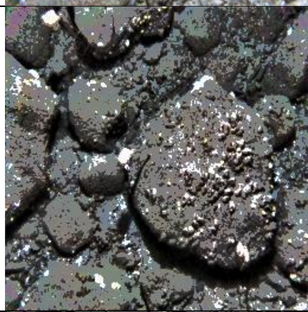
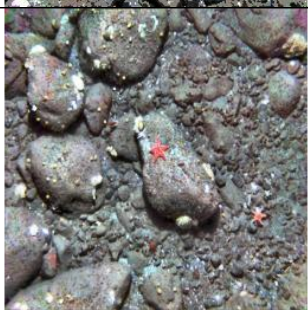
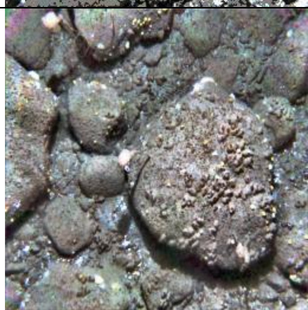
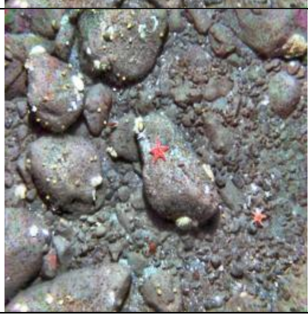
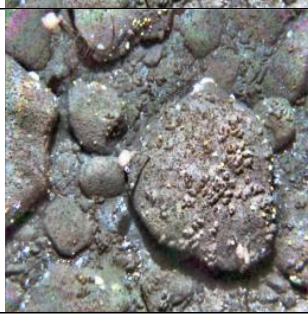
Image result of IGLCC_GA		
Image result of IGLCC_PSO		
Image result of IGLCC_FF		
Image result of IGLCC_CS		
Image result of IGLCC_DOCS		
Image result of IGLCC_DA		

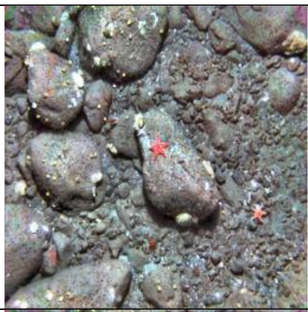
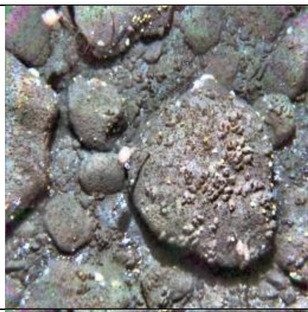
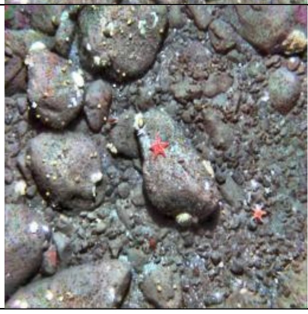
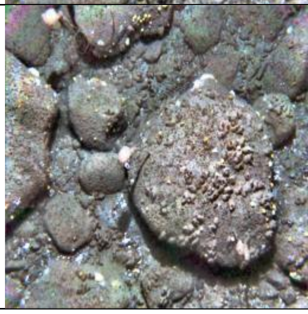
Image result of SU-DA		
Image result of SU-DA		

Fig. 5. Image results on dataset 1 of Proposed and Conventional models (a) Image 1 and (b) Image 2

Original image		
Image result of CLAH		
Image result of Dynamic Stretching		

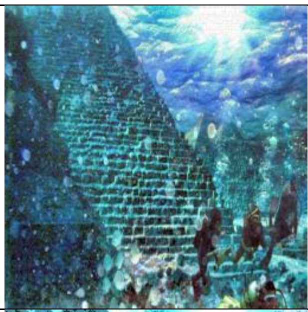
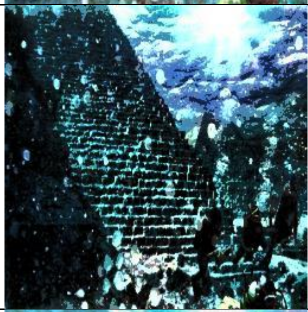
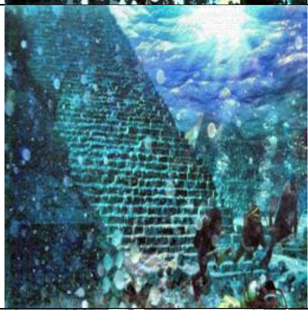
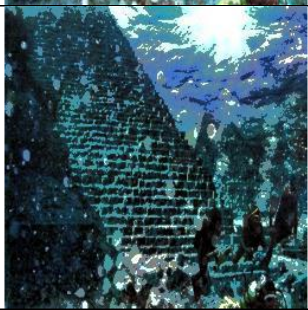
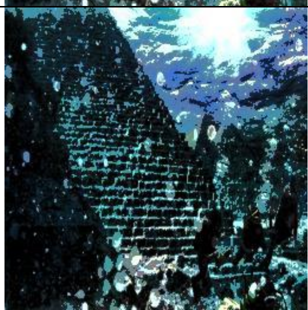
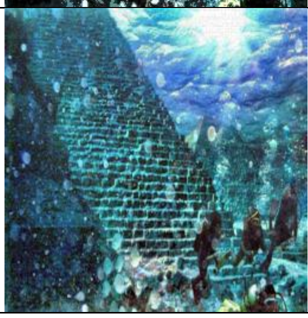
Image result of IGLCC		
Image result of IGLCC_GA		
Image result of IGLCC_PSO		
Image result of IGLCC_FF		
Image result of IGLCC_CS		
Image result of IGLCC_DOCS		

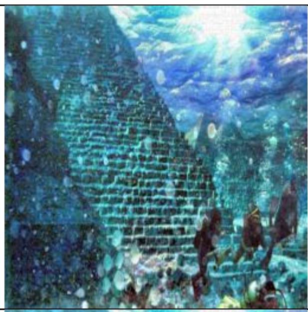
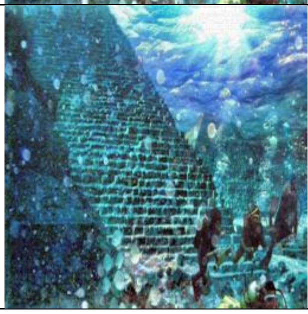
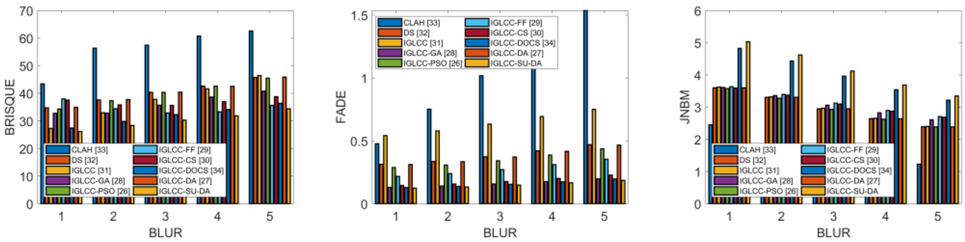
Image result of IGLCC_DA		
Image result of SU-DA		

Fig. 6. Image results on dataset 1 of Proposed and Conventional models (a) Image 1 and (b) Image 2

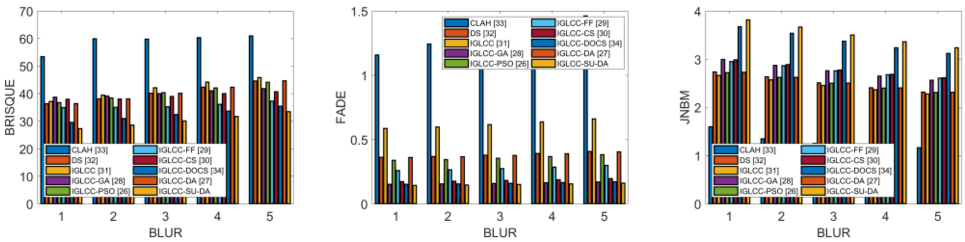
5.2 Performance Analysis

The analysis on performance of the implemented model over the traditional model for three dataset regarding the Brisque, Jnbm and Fade are symbolized in Fig. 7. From the Fig. 7(a), in dataset 1 for the blur value 1 in terms of Brisque measure, the implemented model is 41.65%, 26.94%, 3.8%, 21.3%, 25.22%, 31.61%, 31%, 6.05% and 27.37% better from CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. While considering the blur value 5, the implemented model has attained betterment than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA by 43.46%, 25.58%, 26.79%, 14.62%, 25.92%, 4.41%, 10.51%, 5.84% and 25.07%, respectively. In terms of Fade measure, for the blur value 1, the implanted model has attained superior performance with less fade and that is 62.28%, 51.12%, 63.52%, 45.69%, 36.48%, 7.95%, 0.96% and 49.66% than CLAH, IGLCC, dynamic stretching, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. For the blur value 5, on considering the Jnbm measure, the developed model is 59.57%, 41.24%, 39.85%, 30.49%, 40.66%, 25.77%, 26.94%, 0.95% and 42.07% superior to CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively.

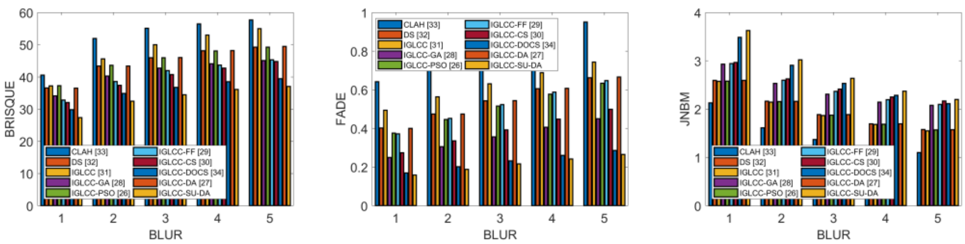
For the dataset 2, from Fig. 7(d), the proposed model in terms of Brisque measure having blur value 5 is 44.89%, 24.1%, 27.28%, 19.3%, 23%, 9.38%, 16.29%, 3.24% and 24.71% better from CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS, and DA respectively. Similarly, for Jnbm measure, the implemented model with blur value 5 has attained the betterment with high Jnbm and that is 65.4%, 35.68%, 47.1%, 16.85%, 41.53%, 13.96%, 13.23%, 2.98% and 32.66% than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. Moreover, regarding the Fade measure, the introduced model has possessed a superior performance than CLAH, IGLCC, dynamic stretching, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA by 84.24%, 49.89%, 69.47%, 71.99%, 38.86%, 7.09%, 2.48% and 71.99%, respectively.



(a) (b) (c)



(d) (e) (f)



(g) (h) (i)

Fig. 7. Performamnce analysis of proposed over conventional models regarding Brique, Fade and Jnbm measures (a) (b) and (c) for dataest 1 (d) (e) and (f) for dataset 2 (g) (h) and (i) for dataset 3

5.3 Statistical Analysis

Because of the stochastic nature of meta-heuristic algorithm, the accurate outcome will not be obtained. Hence, the execution is made for five times and determines based on the best, worst, mean, median and standard deviation. The statistical analysis has been made on the gained outcomes in order to conclude the algorithms efficiency. Table 2 reveals the statistical comparison of implemented over existed models in terms of measures like Brisque, Jnbm and Fade for 1st dataset. From the table, in case of best scenario for the Brisque measure, the proposed model attains less Brisque, and is 19.3%, 11.72%, 3.91%, 3.19%, 4.93%, 87.22%, 10.61%, 2.88% and 3.67% better from CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. In case of mean measure, the implemented model has gained a better performance than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA by 17.47%, 13.57%, 3.23%, 2.02%, 1.84%, 18.8%, 15.93%, 0.2% and 3.97%, respectively. On considering the Jnbm measure, the implanted model in best case has achieved a superior performance and that is 15.35%, 7.82%, 17.34%, 10.13%, 16.13%, 11.09%, 7.2%, 1.61% and 15.17% than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. In worst case scenario, the introduced model is 15.46%, 2.71%, 17.9%, 17.93%, 15.84%, 17.3%, 18.84%, 0.92% and 15.48% superior to CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. for the Fade measure, the implemented model for the best case has attained betterment over the other conventional models CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA by 59.63%, 58.59%, 73.35%, 19.47%, 56.52%, 38.14%, 22.87%, 3.63% and 59.27%, respectively. For median measure, the proposed model is 59.56%, 59.58%, 75.35%, 4.5%, 56.16%, 42.07%, 9.52%, 2.41% and 59.33% better from CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. Thereby, the proposed model performance is proved over the traditional models.

Table 2: Proposed Model for Dataset 1 regarding Brisque, Jnbm and Fade

				BRISQUE						
	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	26.166	18.9	21.974	21.811	22.209	11.278	19.09	21.741	21.92	21.115
Worst	61.159	65.785	40.226	43.458	40.235	48.882	45.355	39.252	40.374	38.664
Mean	39.142	37.372	33.379	32.967	32.906	39.781	38.425	32.236	33.639	32.302
Median	36.301	38.122	33.155	30.453	33.38	43.458	39.483	32.757	33.777	32.428
Std_Dev	10.466	14.084	5.1724	8.5964	5.1195	9.5122	6.7092	4.9509	5.0583	4.7902
				JNBM						
	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	4.1335	4.4219	4.0633	4.3293	4.1056	4.2917	4.4475	4.6921	4.1398	4.7678
Worst	3.4179	3.8423	3.3473	3.3464	3.4067	3.3644	3.3208	3.9104	3.4173	3.9463
Mean	3.7349	4.1062	3.7397	3.7212	3.716	3.7464	3.6981	4.2701	3.7287	4.3093
Median	3.7264	4.0873	3.7545	3.5813	3.7116	3.7107	3.5689	4.2741	3.7164	4.2988
Std_Dev	0.17157	0.1504	0.19496	0.27225	0.17147	0.21898	0.32305	0.19404	0.17803	0.20354
				FADE						
	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	0.15212	0.14831	0.23043	0.076268	0.14124	0.09928	0.079625	0.063729	0.1508	0.061418
Worst	0.41294	0.42799	0.83388	0.17194	0.37248	0.28535	0.18393	0.16774	0.41189	0.16672
Mean	0.30689	0.30071	0.5268	0.12628	0.2804	0.2092	0.13926	0.12613	0.30535	0.12429
Median	0.33474	0.33491	0.54923	0.14176	0.30879	0.23369	0.14963	0.13872	0.33288	0.13538
Std_Dev	0.076924	0.079655	0.15613	0.028511	0.068507	0.058117	0.031948	0.030775	0.076949	0.031135

Table 3 depicts the proposed model analysis on statistical features regarding the Brisque, Jnbm and Fade measures for Dataset 2. On considering the Brisque measure, the proposed model in terms of best case has gained a better performance with least Brisque and is 19.88%, 1.87%, 1.71%, 54.61%, 1.24%, 39.28%, 52.7%, 1.45% and 4.23% than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. For mean case, the implemented model is 30.94%, 28.54%, 3.52%, 25.75%, 4.49%, 27.07%, 27.86%, 3.06% and 4.04% better than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. For Jnbm measure, the proposed model in terms of beast case scenario has gained a superior performance and that is 15.59%, 7.78%, 16.26%, 10.37%, 16.38%, 11.33%, 7.43%, 1.83% and 15.42% than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS, and DA, respectively. While taking the Fade measure, the proposed model regarding the mean measure is 43.91%, 57.45%, 72.07%, 0.43%, 55.03%, 38.84%, 10.99%, 0.21% and 59.63% improved than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively with less fade. Thus, from these result, it is cleared that the implemented model has gained the betterment over the other exiting models.

Table 3: Proposed Model for Dataset 2 regarding Brisque, Jnbm and Fade

BRISQUE										
	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	11.271	8.8639	9.1868	19.894	9.1435	14.871	19.09	8.9005	9.4286	9.03
Worst	61.159	65.785	40.118	43.463	40.063	48.634	43.458	39.252	40.102	38.426
Mean	38.423	37.133	27.503	35.734	27.781	36.384	36.782	27.371	27.651	26.534
Median	37.57	38.122	30.175	39.427	30.229	41.026	37.014	29.594	30.379	28.705
Std_Dev	13.036	14.73	8.6535	8.5976	8.1075	9.8994	6.5238	7.862	8.6082	8.1821
JNBM										
	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	4.1335	4.4333	4.1099	4.3293	4.1056	4.2917	4.4475	4.6921	4.1398	4.7781
Worst	2.7844	3.157	2.5742	3.1733	2.7136	3.0729	3.0854	3.1363	2.7446	3.1496
Mean	3.6207	3.9818	3.5369	3.7837	3.5986	3.7113	3.7492	4.1345	3.6112	4.166
Median	3.6503	4.0197	3.6281	3.7329	3.6146	3.7107	3.6089	4.1694	3.6349	4.2198
Std_Dev	0.33003	0.31301	0.39685	0.3368	0.33339	0.29523	0.37813	0.38036	0.34082	0.39674
FADE										
	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	0.15212	0.14831	0.23043	0.076268	0.14124	0.09928	0.079625	0.063729	0.1508	0.061418
Worst	0.4089	0.42799	0.83388	0.15549	0.37247	0.26618	0.17424	0.16774	0.41121	0.16549
Mean	0.2671	0.26067	0.44188	0.11254	0.24335	0.17855	0.12342	0.10956	0.26474	0.10756
Median	0.27409	0.25638	0.39064	0.10956	0.24256	0.17837	0.12256	0.10932	0.27025	0.10909
Std_Dev	0.067971	0.070839	0.1414	0.022237	0.062586	0.047773	0.025689	0.028077	0.067972	0.02758

Table 4 delineates the statistical performance of the proposed model over the conventional models for dataset 3 in terms of three measures. In terms of Brisque measure, the implemented model has achieved superior performance than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA by

25.86%, 32.48%, 9.28%, 15.71%, 9.4%, 13.92%, 23.03%, 10.78% and 7.13%, respectively. Similarly, for Jnbm measure, in case of worst measure, the implanted model is 15.49%, 3.07%, 13.19%, 16.1%, 14.95%, 25.55%, 26.69%, 0.25% and 15.49% superior to CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. on account of Fade measure, the mean measure performance of the developed model has gained a better solution and that is 59.56%, 59.55%, 67.11%, 34.63%, 56.14%, 55.6%, 40.47%, 3.03% and 59.36% than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS, and DA, respectively. The obtained outcome has revealed the improvement of the proposed model than the traditional models in terms of statistical measures.

Table 4: Proposed Model for Dataset 3 regarding Brisque, Jnbm and Fade

BRISQUE										
	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	20.634	22.657	16.862	13.221	16.885	13.429	12.434	17.147	16.473	15.298
Worst	61.763	62.189	44.037	43.458	44.369	43.459	43.458	42.889	44.095	42.253
Mean	41.69	40.12	29.429	30.108	29.888	29.776	29.41	29.324	29.103	27.949
Median	39.335	40.104	27.944	29.676	28.152	28.883	27.874	27.901	27.45	26.77
Std_Dev	12.87	11.034	7.8092	8.6819	7.9517	8.7605	8.8031	7.6481	7.5818	7.3655
JNBM										
	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	4.6852	5.1646	5.3474	4.4684	4.6419	4.819	4.7794	5.4107	4.7014	5.4467
Worst	1.849	2.0719	1.8866	2.5453	1.8578	2.8683	2.913	2.1408	1.849	2.1355
Mean	3.2754	3.6438	3.2983	3.6157	3.2829	3.5515	3.6269	3.7754	3.2763	3.7857
Median	3.3163	3.7096	3.3069	3.6154	3.3207	3.5021	3.5404	3.8367	3.3223	3.8416
Std_Dev	0.59244	0.65841	0.64322	0.49532	0.58664	0.47379	0.5044	0.68105	0.59266	0.68802
FADE										

	CLAH [33]	IGLCC [31]	Dynamic stretching [32]	ICLCC_GA [28]	ICLCC_PSO [26]	IGLCC_FF [29]	IGLCC_CS [30]	IGLCC_DOCS [34]	IGLCC_DA [27]	SU-DA
Best	0.14479	0.14804	0.12554	0.076268	0.13156	0.09928	0.079625	0.058973	0.14164	0.057211
Worst	0.98167	0.88602	1.4837	0.66059	0.91609	1.0068	0.71166	0.41844	0.97831	0.40195
Mean	0.33968	0.33959	0.41758	0.2101	0.31319	0.30938	0.23071	0.14164	0.33797	0.13735
Median	0.29683	0.30413	0.34876	0.18116	0.28243	0.26989	0.18734	0.1266	0.29678	0.12144
Std_Dev	0.20346	0.19996	0.2788	0.14568	0.19105	0.22598	0.16485	0.087136	0.20315	0.083364

6. Conclusion

In this framework, a novel underwater image enhancement approach has been introduced in order to improve the underwater image quality. Two stages were involved called contrast correction, and color correction. The contrast correction model has two processes called Global contrast correction and Local contrast correction. The optimal histogram selection was considered as the major target for effective enhancement, in the histogram evaluation. Hence, a new SU-DA algorithm has been introduced, which was the hybridization of PSO and DA. Finally, the implemented model has been compared over the other standard existing models in terms of some measures and the results were thus analyzed. In dataset 1 for the blur value 1 in terms of Brisque measure, the implemented model was 41.65%, 26.94%, 3.8%, 21.3%, 25.22%, 31.61%, 31%, 6.05% and 27.37% better from CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA, respectively. While considering the blur value 5, the implemented model has attained betterment than CLAH, IGLCC, dynamic stretching, IGLCC_GA, IGLCC_PSO, IGLCC_FF, IGLCC_CS, IGLCC_DOCS and DA by 43.46%, 25.58%, 26.79%, 14.62%, 25.92%, 4.41%, 10.51%, 5.84% and 25.07%, respectively.

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