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Low contrast detection factor based contrast enhancement and restoration for underwater images

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Marine ecosystem is the largest of earth's aquatic ecosystems. It includes salt marshes, coral reefs, deep sea, sea floor, etc. To learn deep about the activities taking place inside, underwater imaging is a tool. But these images lack in contrast and brightness leading to the lack of information in the ocean activities. To enhance such low contrast underwater images, Low Contrast Detection Factor (LCDF) is proposed in this study. It uses the value, saturation and hue to enhance the low contrast regions and to restore the color. Quality assessment is done to substantiate the proposed algorithm. It is found that the entropy gives an average of 7.3. No-reference Quality Metrics such as Natural Image Quality Evaluator and Blind/ Referenceless Image Spatial Quality Evaluator shows an average value of 3.6 and 22.5, respectively. The blur metrics shows a value of 0.21. The quality metrics indicates that the naturalness of the underwater image is maintained while the contrast of the underwater image has increased.

[**Keywords**: Contrast enhancement, HSV color space, Low Contrast Detection Factor (LCDF), Underwater image]

Introduction

Marine ecosystem, relates to the study of marine life and their adaptations to the habitat. In order to study the marine life, underwater images are taken and are being processed. The brightness and the chromaticity used in defining the contrast of the underwater image make the object distinguishable. The actual colours are subdued, while the dissimilarity is not established between the dark and bright colours in the image. Due to water characteristics, attenuation of light occurs in water which results in low contrast images. Hence, a high frequency emphasis filter is used along with homomorphic filter for contrast enhancement[1]. The present work has incorporated Singular Value Equalization to enhance the contrast of the images[2]. In order to enhance the contrast of the image the Discrete wavelet transform along with Singular Value Decomposition, followed by Histogram Equalization (HE) is applied. LL sub-band is used for processing as it contains the illumination details and this is given by:

$$\xi = \frac{\max\left(\sum_{N(\mu=0,var=1)}\right)}{\max\left(\sum_{I}\right)} \quad \text{... (1)}$$

Where, $\sum_{N(\mu=0,\ var=1)}$ is a singular value matrix[3]. At the initial stage, the histogram of the image is obtained. Geometric mean filter and Histogram Equalization (HE) are then applied to the image to obtain the contrast enhanced image[4]. In order to enhance the contrast of the image, it is split up based on their histogram, and HE is carried out[5]. The image intensities are adjusted based on power law for enhanced contrast[6]. Here, the dynamic stretching is done for contrast enhancement[7]. The value component obtained from the Hue, Saturation, and Value (HSV) color space is enhanced using gamma correction. The image is then converted into L*a*b* color space where the contrast of the image is enhanced in the luminance channel[8]. This technique cannot be used for mid-level intensities[2,3]. Continuous intensity spectrum is used on polarity of local edges. The images are then compressed. The compressed image and the edge guided expansion were combined to preserve the finer details of the images[9]. Morphological transform has been used for enhancing the contrast of the image[10]. Here, Dong has initially inverted the images. The foreground images now have low intensity in one of the channels. This is similar to haze effect present in images. Hence, to overcome this image dehazing is done to obtain illumination enhancing image[11].

The Adaptive Multi-Scale Retinex (AMSR) technique is a combination of number of Single Scale

Retinex with their respective weights. This combination is done to enhance the image contrast[12]. Here, the underexposed region and the well exposed regions of the images are fused along with their weights to enhance the contrast of the image[13] using a combination of camera response model with Retinex model for image enhancement[14]. The Brightness Preserving Dynamic Fuzzy Histogram Equalisation (BPDFHE) initially considers the image grey values to compute fuzzy histogram. The image is then partitioned based on the local maxima in the fuzzy histogram. The partitioned histogram is then individually equalized. Finally, the mean intensity of the image is normalized to preserve the brightness of the image[15]. The technique follows image fusion for contrast improvement. For fusion, three inputs are considered in the technique; where the first input gives the estimated illumination while the second input gives the global illumination. The third input uses contrast local adaptive histogram equalization for contrast improvement. The inputs are then fused with their respective weights to get illumination and contrast enhanced images[16]. Here, the saturation or the intensity of the HSI color space is normalized to [0,1]. It is then converted to RGB color channel to enhance the contrast of the underwater images[17]. Here, Differential Gray-Levels HE for color images an extension of Dynamic Histogram Equalization (DHE) is being used to enhance the contrast of the underwater images. In DHE, the image is split into sub regions based on their histogram values and then HE is done to enhance the contrast of the image[18]. The mean and median values of the image histogram are used as threshold to separate the images into upper and lower histograms. The regions are separately stretched and are then integrated in order to remove over and under illumination of the image[19]. Dynamic Fuzzy based Improved Particle Swam Optimisation is also used to increase the contrast of the images. To this, the Gaussian filter with smaller kernels is initially applied to smoothen the image. The image is then segmented based on their median value. This is then modified using Non-subsampled Contourlet transform based HE to enhance the contrast of the image[20]. It focuses on segmenting the image with reduced dynamic range. The images are then clipped and fused back. These fused images are then rescaled. Finally, the scaled images are once again clipped on both the ends of the histogram to give a contrast enhanced image[21].

The main advantage of AMSR technique is the tonal retention[10]. The main advantage of Hessel *et al.*[21] is it eliminates low frequency halo which is present in Sheet *et al.*[15], while the main detriment is it provides flat region in the images with saturation[21]. Similarly, the main detriment of Rao *et al.*[20] is it can be applied only on grey images whereas; the main disadvantage of AMSR and Dong technique is the images processed by these techniques suffers from contrast distortion[13].

Materials and Methods

Proposed methodology

Underwater images in general suffer from low contrast which makes it hard for the researchers to study, various objects and flora and fauna like coral reefs and fish present underwater. In order to overwhelm this drawback our proposed work concentrates on the enhancement of low contrast underwater images and restoration of the color of these images. The enhancement of such images is required to analyse various underwater objects, to differentiate and understand various species of fishes and for various other applications. Figure 1 gives the proposed work flow.

Simulation setup

The proposed work was carried out in Lenovo T430 laptop with 14” display, Intel(R) Core(TM) i5-3320M CPU @ 2.60GHz, 2601 Mhz, 2 Core(s), and 4 Logical processor(s). Matlab R2017b was used for running the simulation.

Dataset

For the purpose of analysing the proposed work about 25 images have been considered. Underwater low contrast images were taken from two different sources:

1. Kavasidis *et al.*[22], the video is about 2 minutes which was converted into 200 images of dimension 320*240 each.
2. *www.depositphotos.com*, the video is about 14seconds which was converted into 30 images of dimension 608*342 each.

The video streams are generated as a part of an ecological monitoring effect and forms resource base for marine biologists. It gives useful information and makes it accessible to non-programming scientist. The videos are collected from about 10 underwater cameras for about 2 years. For this work, the videos are converted into frames and then further processed[22].

Data pre-processing

For pre-processing, HSV colour space is used as it provides better visual discernment compared to RGB. As the work focuses on low contrast, the saturation and the value channels are considered. The saturation provides the details on the quality of the color and value provides the darkness of the color. The HSV color channels are used for construction of high-quality images.

To prevent the heat flow, the anisotropic filter generates small conductance along the edges and thus preserve the edge properties of the underwater images. Here, the anisotropic filter is used as it evades blurring effect in the underwater images.

Low Contrast Detection Factor (LCDF)

The LCDF is modified from the Normalized Saturation-Value Difference Index[23] equation. The LCDF derived is based on the fact that, in HSV component, the darker areas have lower saturation and lower value components. LCDF is calculated based on the saturation and the value of the underwater image.

Low Contrast Detection Factor,

$$LCDF=(S-V)-(V+H) \quad \text{... (2)}$$

Where, S, V and H represent Saturation, Value and Hue of the underwater image respectively.

Figure 2 shows the output image after LCDF is applied. The threshold value is set by applying global thresholding on LCDF. The LCDF values lesser than the threshold value is considered as low contrast region and pixels with higher values than the threshold value is considered as high contrast regions. The subdivided region is represented by Br for bright and Dr for dark regions. The Vestibule value is computed based on the mean value of the dark region and the pixel intensity of the original image was computed as given in equation (3).

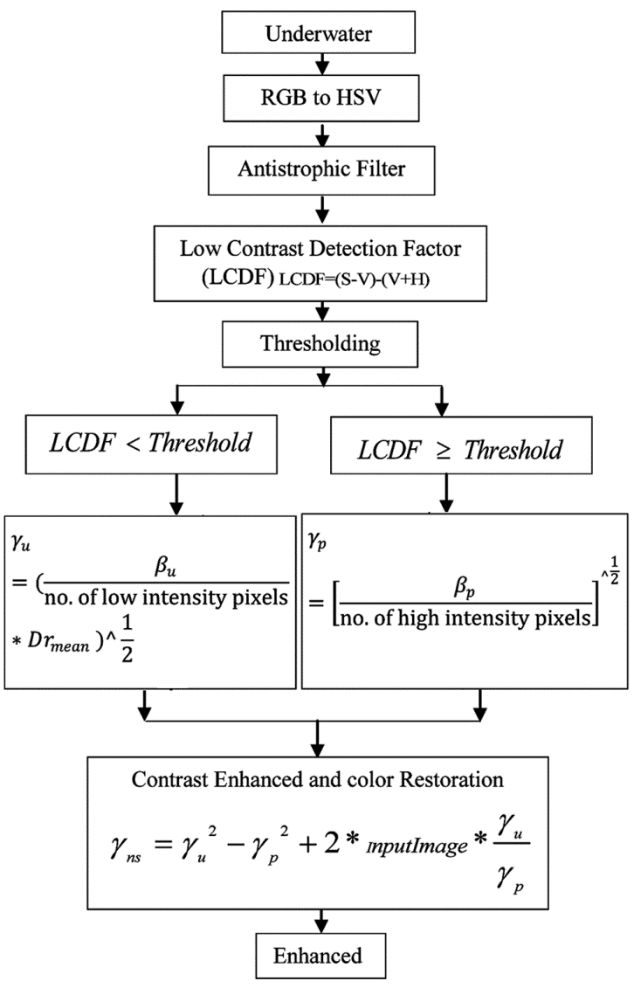

Fig. 1 — Methodology of proposed work

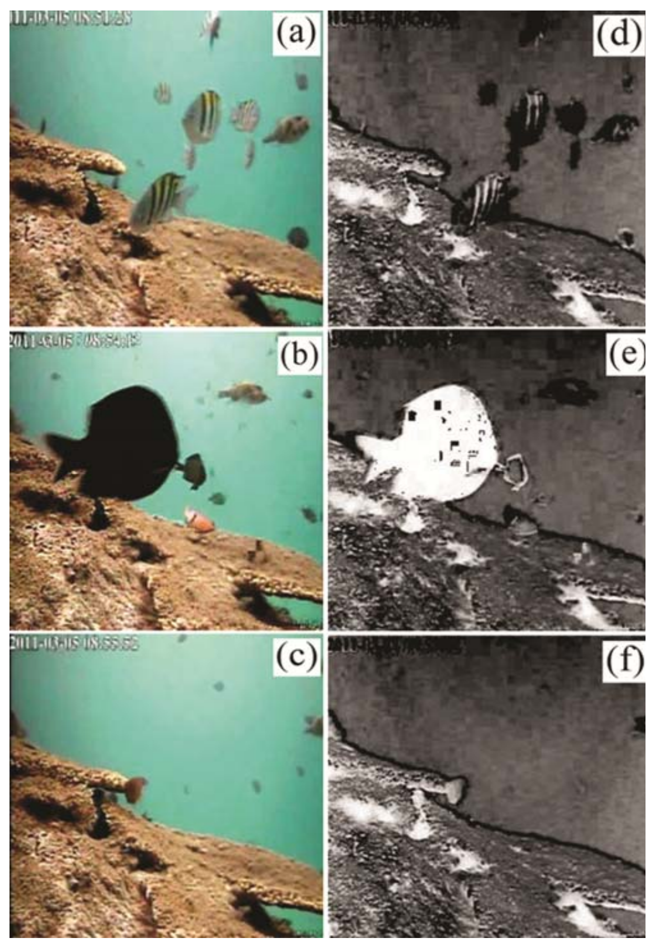

Fig. 2 — (a, b, c) represents the input image, and (d, e, f) represents the image after applying LCDF

Vestibule value, $\nu = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(x_{i,j})*Dr_{(i,j)}}{m*n}$ ... (3)

Where, $x_{i,j}$ represents the intensity of pixels of the image after data pre-processing at i,j; $Dr_{(i,j)}$ represents the intensity of pixels of the dark region at i,j; and m, n represent the image size.

The Vestibule value is then combined with the dark region as it helps in enhancing the sharpness of the image while maintain the illumination of the underwater image.

$$\gamma_u = (\frac{\beta_u}{\text{no. of low intensity pixels}} * \nu_{(i,j)})\wedge\frac{1}{2} \quad ... (4)$$

Where, $\beta_u = \alpha_u + (\text{A-}\frac{\alpha_u}{\text{no. of low intensity pixels}})\wedge 2$ ... (5)

Where, A represents the matrix of the input image.

$$\alpha_u = \frac{1}{4}\sum_{i=0}^{m}\sum_{j=0}^{n}(x_{i,j}) * \nu_{(i,j)} \quad ... (6)$$

Where, $\nu_{(i,j)}$ is the Vestibule value at i,j.

Similarly, for the bright region,

$$\alpha_p = \sum_{i=0}^{m}\sum_{j=0}^{n}(y_{i,j}) \quad ... (7)$$

Where, $y_{i,j}$ represents the intensity of pixels at (i,j) for bright intensity region and m, n represent the number of image size.

$$\beta_p = \alpha_p + (A\text{-}\frac{\alpha_p}{\text{no. of high intensity pixels}})\wedge 2 \quad ... (8)$$

The high intensity of the bright region is given by:

$$\gamma_p = (\frac{\beta_p}{\text{no. of high intensity pixels}})\wedge\frac{1}{2} \quad ... (9)$$

$$\gamma_{ns} = {\gamma_u}^2 - {\gamma_p}^2 + 2x_{i,j} * \frac{\gamma_u}{\gamma_p} \quad ... (10)$$

Where, γ_{ns} represents the contrast enhanced and colour restored underwater images.

From the above-mentioned equations, it is clear that both the image contrast and the illumination of the underwater image have increased considerably. The LCDF helps in finding the threshold required to distinguish the low contrast area where the diversity in the image is clearly visible.

Quality assessment

The performance of the algorithm is subjected using no reference metrics to predict the quality of the enhanced underwater image. The image properties included in the evaluation are of image details and naturalness of images.

Entropy

Entropy gives the quantity of information present in the image. High entropy value represents high image contrast from neighbouring pixels. The entropy value of the images is calculated by:

$$Entropy = -\sum(P_i \log P_i) \quad ... (11)$$

Where, P_i represents the normalized histogram counts.

Natural Image Quality Evaluator (NIQE)

NIQE quality metrics is adopted as given by Mittal *et al.*[24]. NIQE is no-reference based quality assessment and is based on Natural Scene Statistic (NSS). It is an option-unaware and does not use subjective quality scores. It can measure the quality of images with arbitrary distortion. NIQE assesses image quality without the knowledge of anticipated distortions. Lower the NIQE value better the image quality.

Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE)

BRISQUE is a no reference quality metrics[25] based on NSS. It gives the quality naturalness present in the image. Lower the BRISQUE value better the image quality.

Blur Metrics

The blur metrics is calculated based on the intensity values of the neighbouring pixels. The blur metrics is calculated based Oncretea *et al.*[26]. The blur estimation ranges from 0 to 1 where, 0 represents no smoothening in the images, and 1 represents high smoothening effect in the images.

Results and Discussion

The average quantitative results for the underwater images are given in Table S1. Here, 25 images of low contrast of complex background are chosen from the database. The low contrast underwater images processed by the proposed LCDF technique is compared with other techniques. The processed images are given in Figure S1. The individual analysis of these underwater images is shown in Figure 3.

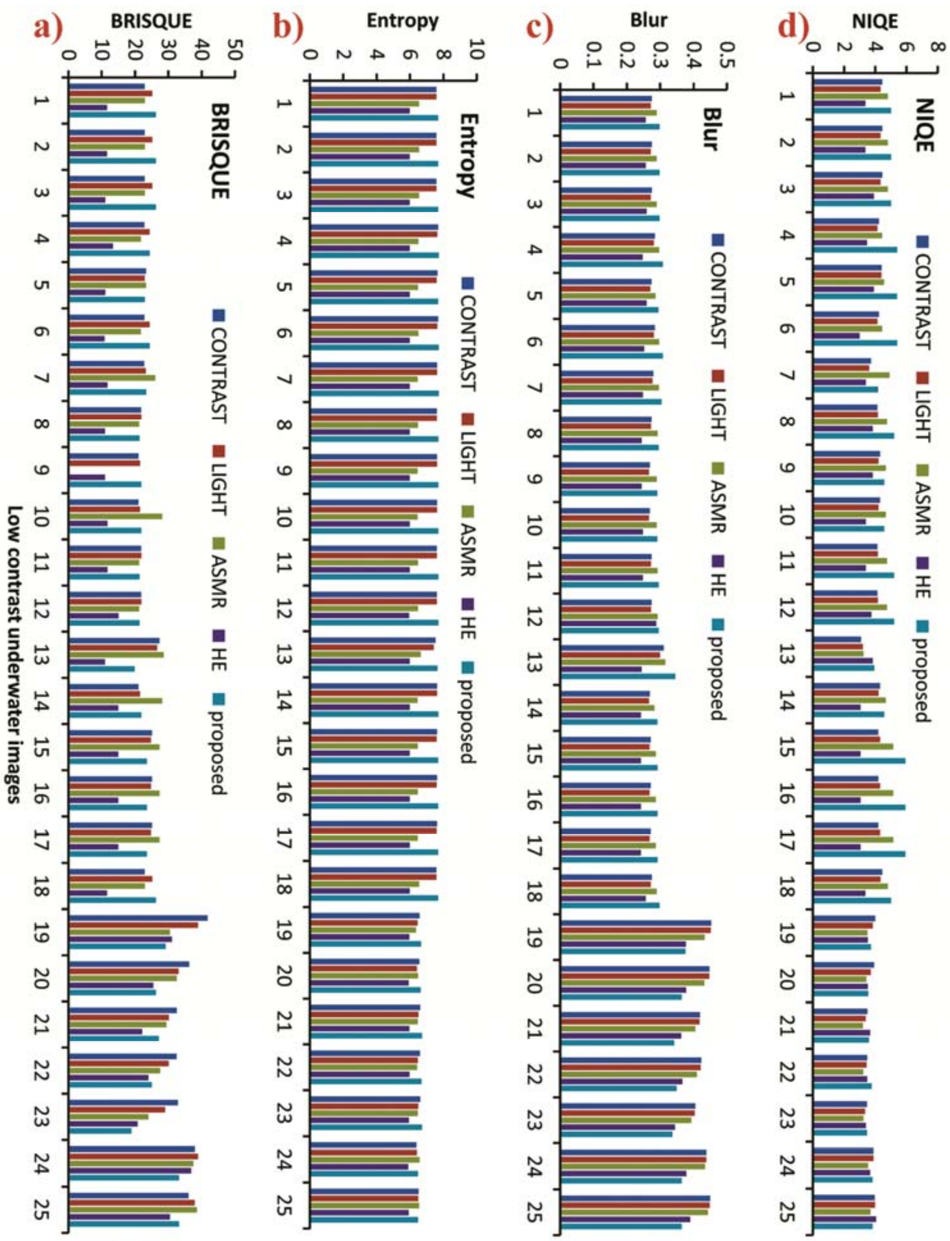

Fig. 3 — Comparison of: a) BRISQUE value, b) Entropy value, c) Blur value, and d) NIQE value; for the images processed by the proposed LCDF and entropy value for images processed by AMSR, Fusion Framework, BPDFHE and Ying technique

From Figure S1 it is quite evident that the illumination and contrast of the underwater image has decreased. As a result, the smoothness of the underwater image has increased. This is backed by the fact that the AMSR gives the highest blur value of about 0.327. Similarly, loss of color information is found in the image 13 of Figure S1. This is backed by low entropy value of about 6.3 and high BRISQUE value of about 28.6 on an average.

Based on Figure S1 it is observed that the images processed by BPDFHE have increased the contrast of the underwater images. Non-uniform illumination is found in images processed by BPDFHE leading to loss of information. This is clearly visible in image 13 of Figure S1, wherein a loss of color information is found in the fish. It also includes pseudo color in the images which is clearly visible from images 19 to 25 of Figure S1. This is backed by a low entropy value of about 5.9 from Table S1. Over illumination is also observed in image 24 of Figure S1 processed by BPDFHE leading to an BRISQUE value of about 36.8 for that image, where the lowest BRISQUE value of

33 is obtained when the image is processed by the proposed LCDF.

Underwater images processed by the fusion framework and Ying technique[14] have enhanced the illumination of the images but slight loss of information is found. This is clearly visible in image 13 of Figure S1 and this is backed by high blur value of about 0.32 and 0.32, respectively for fusion framework and Ying technique[14]. Whereas the lowest blur value for the image is obtained at 0.21.

According to Figure S1, the proposed LCDF based contrast enhancer had better contrast compared to the other algorithms given in this paper while maintaining the naturalness of the underwater images. This is backed by the lowest NIQE and BRISQUE value on an average of about 3.6 and 22.5, respectively. It is also observed that the sharpness of the underwater images processed by the proposed LCDF based contrast enhancer has increased. This is backed by low blur value of about 0.21.

Hence it can be concluded that although images processed by BPDFHE shows an increase in contrast, the technique also enhances the underwater images. While there is not much contrast enhancement is observed in fusion framework and Ying technique[14]. Smoothness is found in images processed by AMSR whereas; the proposed LCDF based factor enhances the contrast of the underwater images. It also maintains the naturalness of the images.

Conclusion

The proposed work is based on the LCDF which is used in dividing the underwater images based on their contrast level and enhances the contrast of the images on the basis of their intensity level. Thus, the proposed work is vital in enhancing the marine underwater images. From the quality metrics it is understood that the images have been enhanced significantly. Although the main idea behind the proposed work was to enhance the contrast of the image and restore the color of the underwater image it is found that both the sharpness as well as the illumination of the image has increased considerably. In future we will focus on automatically detecting the low contrast images from non-degraded underwater images and contrast enhancement for the same.

Supplementary Data

Supplementary data associated with this article is available in the electronic form at http://nopr.niscair.res.in/jinfo/ijms/IJMS_50(01)7-13_SupplData.pdf

Conflict of Interest

There is no conflict of interest.

Author Contributions

The first author (AB) was involved in the conceptualization, analysis and writing the manuscript. The second author (OUM) supervised the work throughout.

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