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ENHANCING UNDERWATER IMAGE VISIBILITY USING HARMONIC MEAN FILTER AND DEEP WEIGHTED MAP

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ABSTRACT
Underwater images are characterised by low visibility while light is continuously attenuated as it passes through the water, resulting in scenes that are inadequately contrasted as well as noisy. The main objective is to remove noise from underwater images and enhance the visibility of an image by restoration method. A harmonic mean filtering (HMF) is used for removing Gaussian type noise as well as restoring and then Deep Weighted Map (DWP) is used for smoothing. Harmonic mean filter simultaneously removing positive outliers. A denoising technique (HMF-DWP) is implemented in this research to remove additive noise from underwater imagery. In the trials, the suggested method's denoising outcomes were compared and assessed against image data denoising methods that focus on PSNR and MSE. The results shows that the suggested underwater approach outperforms previous denoising methods.
Keywords: Underwater Image, Denoising, Harmonic Mean Filtering, Deep Weighted Map, PSNR, and Image Enhancement.

1 INTRODUCTION
The marine stream's study area trends have recently risen. However, in order to operate on aquatic items, good images of the underwater components are required [1]. As the air interfaces deals with environmental and camera issues such as dust particle, natural sunlight, reflection, focus, and distance, underwater images do as well. Underwater image quality is affected by water density, depth, range between camera & object, artificial light, water particles, and other factors [2]. As the depth increases, the water gets denser due to sand, planktons, and minerals. As particle density rises, camera light deviates back and is deflected by particles for some moment along the journey to the camera, while the remaining camera light is absorbed by the particles [3]. This scattering effect reduces the visibility of low-contrast images. Furthermore, the colour change effect is affected by the wavelength of light that travels through the water.
Image enhancement techniques can be optimized by modeling degradation to improve image quality while reducing hardware costs [4]. Artificial lighting of light on the item may extend the visibility range, as well as forms a brilliant spot in the centre of the image with a weakly lighted region around it. When the quantity of light decreases; colours fade depending upon their wavelength [5]. Because blue has the shortest wavelength, it goes the farthest in water.

Underwater images suffer from poor contrast, bright artefacts, non-uniform illumination colour reduction and noise. Due to the various distortions, underwater image restoration is a difficult challenge [6]. The major causes of information degradation are 1) light scattering, 2) wavelength dependent colour attenuation, and 3) object blurriness.

Images shot under water often suffer from quality deterioration issues such as poor contrast, blurring details, colour variations, non-uniform lighting, and so on. The restoration and improvement of underwater images is a critical subject in image processing & computer vision, with several practical applications [7]. Underwater image repair and enhancement has attracted an increasing amount of study attention over the previous several decades. Although significant advances in the broad field of image enhancement and restoration have recently been achieved [8].

The following are the remaining portions of the paper: Section 2 addressed relevant papers, Section 3 described the suggested approach, Section 4 gave experimental data, and Section 5 concluded the methods.

2 RELATED WORKS

The improvement approach that has been suggested includes three stages: In the spatial domain, automatic white balancing, contrast enhancement, and Chromatic stretching are used. Each of these stages is performed in turn. The colour cast in underwater images may be removed using a process called automatic white balance [9]. The haze removal algorithm is effective in overcoming the haziness, but at the expense of reducing the local contrast and giving the impression that the image is lacklustre. In this study [10], a unique approach of image dehazing is created. This method integrates optics with image processing technology in order to get the desired results.

The datasets that are being investigated have been gathered on a variety of environments with varying levels of ambient light, such as fishery tanks, ponds, and lakes, so that the suggested algorithm would be as flexible as possible. The thresholding as well as masking approach [11] may be used to improve the appearance of an image's foreground region. In the restoration [12], a global-local stochastic process is incorporated with the purpose of bridging the gap among synthesized and real-world images. Furthermore, visual data is incorporated into the process to enhance understanding of the content of the surroundings.

In this paper [13], it was suggested to solve the aforementioned degradation concerns by correcting the attenuated colour channel and enhancing the contrast while preserving the detail. The root filtering method emphasises high frequency terms associated with boundaries and texture with smaller amplitudes while de-emphasizing frame spectral analysis [14]. This is performed by splitting the incoming signal in half.

In actual use, the improved images could not improve the efficiency of the detecting process at all, and they might even cause a significant decline in performance. This work [15] proposed an entity twin adverse contrastive learning-based underwater improvement system with the objective of attaining both sense of sight and task-oriented enhancement [16]. As a result of this separation, we are able to make use of a soft-thresholding operation in order to reduce the amount of noise in the high-frequency component.

However, unclear features and unnatural colour continue to be a barrier for the effectiveness of retinex variational models when applied to the improvement of underwater images [17]. In order to circumvent these restrictions, a hyper-laplacian reflectance priors inspired retinex variational model was presented as a means of improving underwater images. In this study [18], a unique approach for dehazing underwater images was reported. The images were dehazed using this approach, which estimated the global foreground light based on the optimal eigenvector of a matrices that had been constructed.

Because of light absorbs and disperses as it passes over water, underwater views often endure from blurring, fogging, poor resolution, and speckle noise [19]. These issues are caused by the water's interaction with the light. In order to address important difficulties, we developed a unique framework that improved image quality in the frequency domain by integrating variational approaches with pyramid technology [20].

3 PROPOSED METHODOLOGY

In the proposed methodology, scene depth is estimated to be constant, and the remaining parameter is obtained by considering different conditions. A noisy underwater image is given as input and an image is processed in background subtraction with initial background separation as well as secondary data collection. Then HMF is applied for removing Gaussian noise from an image and restoring it. After that it is processed in DWM method for noise elimination and smoothening of an image which requires presence of weights. Finally an enhanced denoisy underwater image is generated as output and parametric evaluation is calculated by obtained results of MSE and PSNR value. The overall process of proposed methodology is shown in fig 1.

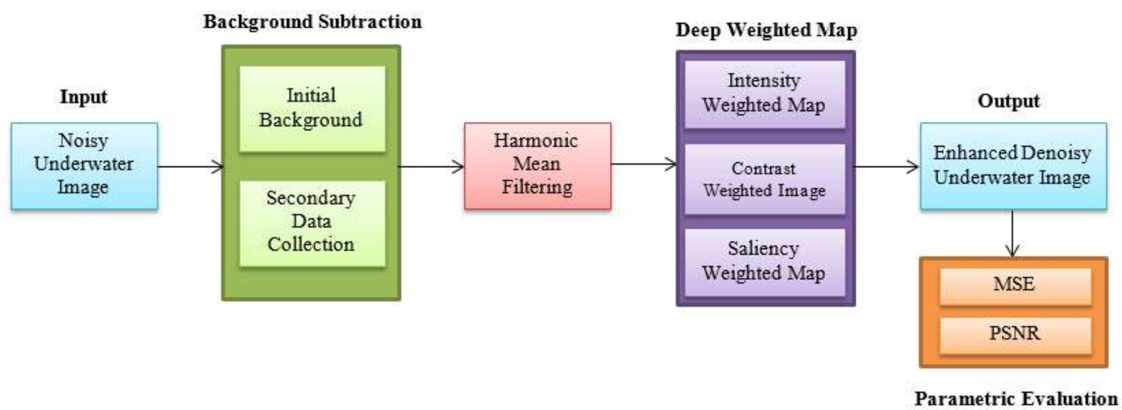

Figure 1. Overall Process of Proposed Methodology

3.1 Harmonic Mean Filter

HMF is one of the mean filters we use to process image data in spatial domain. In this approach, each pixel's grey value is updated using the harmonic mean of neighbouring region. This method is used to create more natural looking images. Applies a HMF to an image and it is defined as in eq 1:

$$HMF = \frac{x}{\frac{1}{n_1} + \frac{1}{n_2} + \ldots + \frac{1}{n_k}} \qquad (1)$$

Where x is the size of the pixel and n_k is the iteration of the pixel. With the help of this function, the image will be filtered using the nonlinear harmonic mean approach. This function is only applicable to black-and-white images that have 8 bits per bixel or 24 bits per pixel. The arithmetic mean filter is superior to the set of nonlinear mean filters that include the harmonic mean filter. These filters are superior in their ability to eliminate Gaussian-type noise and preserve edge characteristics. The harmonic mean filter does an excellent job of eliminating positive outliers from the data. The following equation gives the definition of the harmonic mean filter size:

$$HMF\ (size) = \frac{x}{\sum_{(a,b)} \frac{1}{x(i+a, j+b)}} \qquad (2)$$

where the coordinates $i + a, j + b$ are specified over through the image x and y are defined over the square mask that is N by N in size. It is helpful to use a harmonic mean filter to get rid of impulses that are on the higher end of the intensity range. The arithmetic mean filter is superior to the set of nonlinear mean filters that include the harmonic mean filter. These filters are superior in their ability to eliminate Gaussian-type noise and preserve edge characteristics.

Gaussian Noisy Image

Gaussian noise is defined as noise with a probability density function (PDF) similar to that of the normally distributed, commonly known as the Gaussian distribution. The random variable z's probability density function pdf is given by eq 3:

$$PDF(HMF) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \qquad (3)$$

Where μ denotes the average value, z signifies the color space, and σ is the standard deviation. Gaussian noise is statistical noise. It is distributed over the signal. It is usually used to additive white Gaussian noise. The formation of noise in image processing and computer vision application is modeled as given in eq 4:

$$D(a,b) = R(a,b)m(a,b) + B\big(1 - m(a,b)\big) \qquad (4)$$

where *D* is the image to be denoised, *R* is the scene radiance, B is the underwater light or also referred to as homogeneous background light, (*a, b*) is the pixel coordinates, and *m* is the underwater medium of transmission. The objective of the image restoration model is to obtain *R*,B, and *m* from *D*.

3.2 Deep Weighted Map

The existence of weights is required in order to implement the suggested approach for the removal of noise and smoothing of an image. The reduction of spatial bias begins with the assignment of weights to each pixel according to its proximity to the centre pixel. These weights are determined using the equation stated in step 5 of the process.

$$dist(a,b) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{-d^2}{2\sigma^2}} \qquad (5)$$

Where $dist = \sqrt{(a - a_c)^2 - (b - b_c)^2}$ is the difference between the neighboring pixels (a, b) and the result image of centre pixel (a_c, b_c) when the filter is applied. By applying gaussian smoothing filter as discussed, we can approximate the haze component. This approximation is dependent on the amount of blur.

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \times \begin{bmatrix} b_1 \\ b_2 \\ \cdots \\ b_n \end{bmatrix} \Rightarrow \begin{bmatrix} b_1a_{11} & b_1a_{12} & \cdots & b_1a_{1n} \\ b_2a_{21} & b_2a_{22} & \cdots & b_2a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ b_na_{n1} & b_na_{n2} & \cdots & b_na_{nn} \end{bmatrix}$$

Here generate two depth maps obtained using experimentation, based on visual outcome. The transmission maps is then obtained by eq 6,

$$m\,(a,b) = 1 - b\{dist\,(a,b)\} \qquad (6)$$

where (0<b <1) and is included to retain some element of haze to render natural appearance. Computing the weighted centroid according to the equation 7 is all that is required to convert a filtering window into a vector that can be represented as W.

$$\vec{W} = \sum_{a,b} b_{a,b}\, \overrightarrow{dist}_{a,b} \qquad (7)$$

where $\overrightarrow{dist}_{a,b}$ is the radial vector from the center to coordinates $(a, b)$and $b_{a,b}$ is the weight at (a, b).

Algorithm for HMF-DWM:

Input: Underwater Noisy Image
Output: Enhanced Denoisy Underwater Image

Step 1: Input Image (n x n)
Step 2: Convert RGB to Grayscale image
Step 3: Initiate Background subtraction and collect secondary data
Step 4: Encounter Gaussian noisy data from an image and calculate PDF by Gaussian distribution as:$PDF(HMF) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$
Step 5: Calculate pixel coordinates (a, b) and construct weighted Map matrix for (n x n) pixel
Step 6: Calculate central pixel distance as $dist = \sqrt{(a - a_c)^2 - (b - b_c)^2}$
Step 7: Calculate weighted centroid by,

$$\vec{W} = \sum_{a,b} b_{a,b} \overrightarrow{dist}_{a,b}$$

Step 8: Convert the image into 0-255 color range type
Step 9: Calculate PSNR and MSE for Denoisy image

It is possible to forecast a window size by iteratively increasing the scale factor up to the point when the lowest and maximum pixel values of two successive windows are equivalent. If the pixel is noisy, then it'll be restored by taking a weighted average of the specified window's values; otherwise, the original values of the pixel will be preserved. When doing an analysis based on the pixel density function, a noisy image of size nxn is taken into consideration.

4 EXPERIMENTAL RESULTS

On MATLAB R2019b, a series of tests utilising the suggested approach for HMF-DWM denoising were carried out. The setup of the computer system is a workstation with an Intel Xeon processor E5 1620 v4 operating at 3.5 GHz, 64 gigabytes of random access memory (RAM), and Windows 10 installed on it. The results of the simulation are shown in Figure 2-5. The noisy input image of the undersea scene is shown in Figure 2.

Figure 2. Input Image

Background subtraction seems to be a segmentation process that divides a visual into foreground as well as background separately. It separate initial background data and secondary data from a given image as shown in fig 3.

Figure 3. Background Subtraction

The proposed method takes three weight maps of pixel position (a,b) that specify the intensity, contrast, and saliency to smoothen the output of HMF and to remove noisy data from an image as shown in fig 4 (a) and (b).

(a) **(b)**

Figure 4. (a) Output from Harmonic Filter (b) Deep Weighted Map

Finally an output is generated with denoisy data and enhanced an image as shown in fig 5.

Figure 5. Enhanced Denoisy Underwater Image

4.1 Evaluation of the model

MSE is calculated by taking the average of the squared intensities of the pixels that make up both the original (input) image and the resulting (output) image. According to equation 8, the difference in inaccuracy between the original image and the deformed image is denoted by the notation a(x,y)-b(x,y).

$$MSE = \frac{1}{ab}\sum_{x-1}^{a}\sum_{y-1}^{b}[a(x,y) - b(x,y)]^2 \qquad (8)$$

PSNR also known as the Signal–to–Noise Ratio (SNR), is a quantitative measure of image quality depending on the pixel difference of the two images. The SNR metric estimates the quality of the reconstructed image in comparison to the original image. PSNR is specifically defined in eq 9:

$$PSNR = 10log_{10}\frac{255^2}{MSE}\ (dB) \qquad (9)$$

The value 255 denotes an 8-bit image. When all pixels value is closer to the greatest feasible value, the PSNR is equal to the SNR.

Table 1 contains the results obtained by applying Gaussian noise with a mean of zero and a variance of 0.01 when applied to a standard image size of 256 by 256 pixels.

Table 1: MSE and PSNR of the existing filter image as well as the proposed one using HMF-DWM filter.

Filter Name	PSNR	MSE
Geometric	67.634	0.165
Median	68.12	0.148
Arithmetic	71.235	0.136
Harmonic mean	72.356	0.156

HMF-DWM (Proposed)	74.568	0.0113

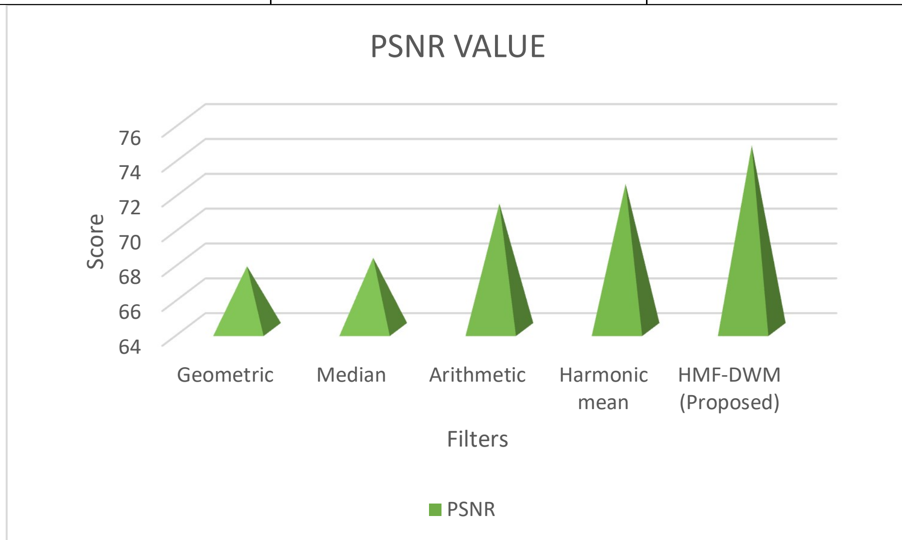

Figure 6. Comparison of PSNR Value

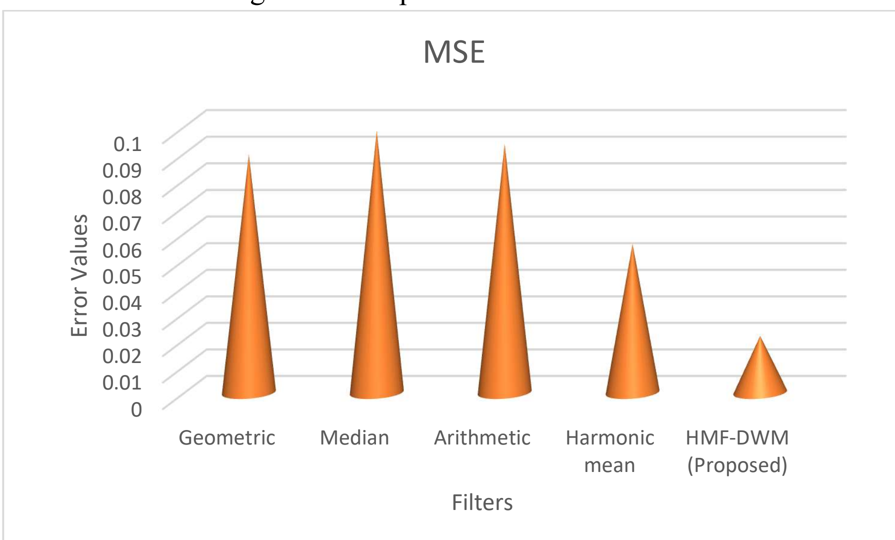

Figure 7. Comparison of MSE Value

From our experimentation as shown in fig 6 and 7, it demonstrated that HMF-DWM greatly improves the denoising performance and enhance the underwater images. The results make it abundantly evident that the approach that was presented is an improvement over the previous filtering method.

5 CONCLUSION

Image denoising and enhancement methods were employed in this research to remove additive noise from underwater images. Firstly a Gaussian noise were removed and restored an image by HMF and then smoothening by DWM. By calculating pixel coordinates and constructed weighted map for measuring distance of central pixel as well as centroid of deep weighted map. The proposed method takes three weight maps of pixel position (a,b) that specify the intensity, contrast, and saliency to smoothen the output of HMF and to remove noisy data from an image.

Finally calculated performance evaluation of the proposed model by PSNR and MSE. A comprehensive analysis found that the HMF-DWM approach utilised for under water imagery improved visibility significantly when compared to other dehazing techniques.

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