UNDER WATER IMAGE ENHANCEMENT USING HYBRID INTELLIGENT OPTIMIZATION

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***Abstract*-Light scattering and color change are two major sources of distortion for underwater photography. Light scattering is caused by the incidence of light on objects reflected and deflected multiple times by particles present in the water before reaching the camera. This in turn lowers the visibility and contrast of the image captured. Color change corresponds to the varying degrees of attenuation encountered by light traveling in the water with different wavelengths, rendering ambient underwater environments dominated by a bluish tone. No existing underwater processing techniques can handle light scattering and color change distortions suffered by underwater images, and the possible presence of artificial lighting simultaneously. This thesis proposes a novel systematic approach to enhance underwater images by a dehazing algorithm. The novel idea proposed in this method is to use color transfer to transform images into the same color space in order to reduce lighting in homogeneities which optimize grasshopper optimization after that threshold which come from optimization used by total variation and enhance the underwater image. The analysis of the proposed model by PSNR and MSE parameters is done and is compared with existing approaches.**

***Keywords: Digital image processing,* Contrast limited adaptive histogram equalization, Bilateral Filtering.**

I. INTRODUCTION

In last few years, underwater imaging is an interesting area of research for the researchers. The reason behind this is that underwater images are used in different fields as well as existing systems. This field includes discovery of objects in the water and image analysis to identify the targets submerged in a liquid. This type of research is helpful for the underwater exploration and defense applications. In this type of studies various approaches of image processing is used for image enhancement [1-4].

Various domain techniques in digital image processing

- ***Spatial domain:*** In this technique, we directly deal with the signal or image matrix to produce an output image. The pixel values changes with respect to scene. A direct manipulation of pixels is performed in an image. It is used for smoothing filters, sharpening filters, un-sharp masking and laplacian.
- **Frequency domain:** Unlike spatial, this technique analyses signal with respect to frequency. The image is transformed to its frequency distribution. The output of this processing is a transformation rather than an image. An inverse transformation is performed to produce an image which, in result, is viewed in spatial domain.
- **Time domain:** It is continuous, infinite domain. In this the measurement is a function of time. One axis that plots the signal is time while the other is amplitude that gives time-amplitude representation of signal as an output.
- **Temporal domain:** It is ratio or relative interval between the events which contains information about the distance between events relative to the distance between other events rather than the frequency and sequence.

1.1 Underwater Image Enhancement

It is the process of enhancing image quality underwater by de-noising. Underwater images are categorized by their poor visibility due to the light attenuation inside the water, which results in images with low brightness and low contrast Therefore, processing of such images is needed to improve the quality and to retrieve the information. Major work has been done in Image Color Correction and Image Enhancement to improve the quality of image. Digital image processing is a broad subject who includes the complex mathematical functions and procedures but it is very simple idea for images [2, 3]. The main aim of DIP is to understand the information, interpret the images. This process is implemented in many areas of science and engineering. Underwater images are affected by illumination, external noise and temperature fluctuations [4, 5].

1.2 Image Restoration

Visibility restoration is a process which belongs to reduce of removes the deterioration or degradation of images that have occurred due to relative camera motion, mis-focus of camera and atmospheric condition etc. In this part we are discussing on degradation occurred due to bad weather and in Haze weather conditions. Degradation in images also occurred due to scattering of light before reaching the camera due to large amount of suspended particles present in the water. This thing affects the monitoring system and smart transportation system. Scattering is occurred due to basic phenomena like attenuation and air light. Removal of Haze of fog from the image improves the robustness and stability of the visual system. It is a difficult task because fog depends upon unknown scene depth map information. Fog effect is the result of distance between camera and object. Hence removal of fog requires the estimation of air light map or depth map. The current haze removal method can be divided into two categories: (a) image enhancement and (b) image restoration. This method can enhance the contrast of haze image but loses some of the information about image [7] [8, 9].

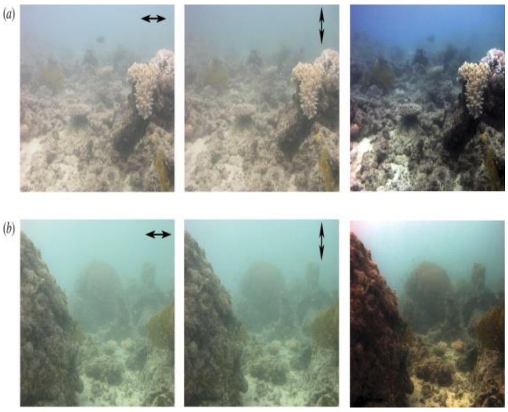

Figure 1.1: Visibility Restoration

1.2.1 Typical techniques of image restoration

1. CLAHE: Contrast limited adaptive histogram equalization short form is CLAHE. CLAHE is [12] used for enhancement of low contrast images. It does not require any predicted weather information for processing of fogged images. Firstly, the image captured by the camera in foggy condition is converted from RGB (red, green and blue) color space is converted to HSV (hue, saturation and value) color space. The images are converted because the human sense colors similarly as HSV represent colors.

Figure 1.2: CLAHE Effect

2. Bilateral Filtering: Bilateral Filtering is used for the edge smoothening and preserves the edges with non-linear combination of nearby values. This filtering is non-linear, simple and local. Gray levels or colors are combined by the bilateral filter based on both their geometric closeness and their photometric similar, and prefers close values to distant values in both domain and range. Bilateral filter smooth edges towards piecewise constant solutions. Bilateral filter does not provide stronger noise reduction. Figure (3) illustrates the processing of foggy image and establishment of it into original image by using bilateral filter.

Figure 1.3: Bilateral Filtering

3. Dark Channel Prior: This techniques is used to estimate the atmospheric light in the dehaze image to get the real result [13]. It is mostly used in non-sky patches, in one color channel have very low intensity at few pixels.In dark channel prior we use pre and post processing steps to get good results. In post processing steps we use soft matting or trilateral filtering etc.

4. Trilateral Filtering: This filtering smooth's images without influencing edges, by means of a non-linear combination of nearby image values. In this filter replaces each pixel by weighted averages of its neighbour's pixel. The weight allotted to each neighbour pixel decreases with both the distance in the image plane and the distance on the intensity axis. This filter helps us to get result faster as compare to other. While using trilateral filter we use pre-processing and post processing steps for better results. Histogram stretching is used as post-processing and histogram equalization as a pre-processing.

1.3 Underwater Degradation

A major difficulty to process underwater images comes from light attenuation. Light attenuation limits the visibility distance, at about twenty meters in clear water and five meters or less in turbid water. The light attenuation process is caused by the absorption (which removes light energy) and scattering (which changes the direction of light path). Absorption and scattering effects are due to the water itself and to other components such as dissolved organic matter or small observable floating particles. Dealing with this difficulty, underwater imaging faces to many problems. First the rapid attenuation of light requires attaching a light source to the vehicle providing the necessary lighting. Unfortunately, artificial lights tend to illuminate the scene in a non-uniform fashion producing a bright spot in the center of the image and poorly illuminated area surrounding. Then the distance between the camera and the scene usually induced prominent blue or green color (the wavelength corresponding to the red color disappears in only few meters). Then, the floating particles highly variable in kind and concentration, increase absorption and scattering effects: they blur image features (forward scattering), modify colors and produce bright artifacts known as "marine snow. At last the non stability of the underwater vehicle affects once again image contrast. Our pre-processing filter has been assessed on natural underwater images with and without additional synthetic underwater degradations as proposed in. Underwater perturbations we added are typical perturbations observed and they have been tested with varying degrees of severity. We simulate blur and unequal illumination using Jaffe and Mc Glamery's model, Gaussian and particles noise as additive contributions to the images and finally reduced color range by histogram operation.

1.4 Underwater Visibility Estimation & Image Enhancement

The goal of this research is to allow real-time enhancement of underwater images which are naturally lit and degraded due to relatively high turbidity and other visibility reducing phenomena. Enhancement of underwater images requires modelling and estimation of the water absorption and scattering characteristics to remove haze. However it also requires a scene depth map. Many papers use a single image and the dark channel prior in the estimation of a depth map. In our approach, we use stereo images in a two-stage enhancement process to improve overall image quality allowing visibility and range estimation [8,9,13].

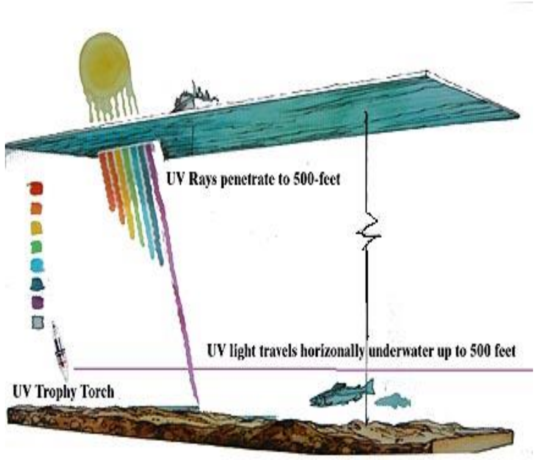

Figure 1.4: Underwater Light Model

Underwater Light Propagation Modelling Underwater light models generally follow a standard attenuation model [1] to accommodate wavelength attenuation coefficients. In this study the Koschmieder Model was adopted which has been established as a description of the atmospheric effects of weather on the observer. In outdoor clear weather conditions, the radiance from a scene point would reach the observer nearly unaltered. However when imaging underwater the irradiance observed by each pixel of the camera (E) is linear combination of directly transmitted scene object radiance that will be attenuated in the line of sight and scattered ambient light towards the observer as depicted in Figure 4.Water splitting is an important reaction that can be used to harvest and store solar energy. In nature, the process produces reactive protons, building up a concentration gradient to power dark reactions which turn CO_2 to organic molecules. In laboratories, a simplified version of the reaction has been conceived to produce O_2 and H_2, the latter promising a solution to problems caused by the combustion of fossil fuels. In a variation, artificial CO_2 reduction can in principle be powered by sunlight to produce solar fuels. Although the detailed chemical mechanisms of these reactions vary, they share the same key features of harvesting solar energy and storing it in chemicals. Essential components necessary to enable the conversion include an antenna to absorb photons and to produce excited electrons, a mechanism to physically move the excited electrons away from the site where they are generated, and an efficient catalyst to drive chemical reactions selectively [1, 6]. Because of the existence of a band gap and the typical band bending formed when in contact with an electrolyte, semiconductors are good candidates for solar water splitting or CO_2 photo reduction. Other appealing aspects of using semiconductors for solar fuel for an underwater image, the radiance of the scene point attenuates exponentially with the propagating distance, according to Beer–Lambert law. The light attenuation in water is caused mainly by absorption and scattering. From red to violet, the wavelength becomes shorter gradually. According to the selective absorption of water, visible light is absorbed at the longest wavelength first. So red light is much easier to be absorbed than shorter wavelengths such as the blue and green. On the other hand, based on Rayleigh scattering theory, scattering intensity is inversely proportional to the fourth power of wavelength, so that shorter wavelengths of violet and blue light will scatter much more than the longer wave-lengths of yellow and especially red light.

II. RELATED WORK

Haofeng, H. et. al [1] underwater images are degraded by scattering of light and noise in the water. In this work polarization information is used which has efficiency to improve the quality of image in scattering medium. Non-uniform optical field image recovery method is proposed in this paper. This method enhance the quality of image and gives better performance from existing method. **Yafei, W. et. al [2]** Underwater image enhancement is done by using wavelet decomposition. In frequency domain fusion based strategy is applied. This fusion process gives two inputs that are color corrected and contrast enhanced images which are extracted from the original underwater image. These images are divided into low and high frequency component by wavelet operator. Average weight is given to the low frequency for fusion and high frequency component by Multi-scale fusion process. **Rahul, R. et. al [3]** Underwater imaging is done to explore the underwater image environment. These images are used for microscopic detection, mine detection, telecommunication cables, and underwater vehicles. These images are disrupted by noise, color distortion and scattering of light which causes blurness and greenish tone. Underwater image enhancement is divided into two methods that are image dehazing and image color restoration. This paper presented a detailed survey of the approaches and methods that used in underwater image enhancement and summary on underwater image processing methods. **Yan-Tsung, P. et. al [4]** underwater image restoration is done on image blurriness and light absorption. In this paper, the author proposed depth estimation method for this work. Images are restored and enhanced by using Image Formation Model. It also estimates the maximum intensity of prior and dark channel prior. The depth of underwater scenes is estimated accurately by this method. **Yue, et. al [5]** Image segmentation of underwater images is done in this paper by using co-saliency and local statistical active contour model. Co-saliency is detected by using cluster-based algorithm; it highlights the silent region of the image. Segmentation of the image is done by using region-based level set method. The proposed method of segmentation provides efficiency and quality of underwater images. **Ghani, et. al [6]** introduced a technique for contrast and visibility improvement in underwater images. Basically it is an integrated approach of enhanced background filtering and wavelet fusion methods. This approach minimizes the negative effects of color cast and low cast. It also improves the visibility and contrast of the image. It provides an effective way for detection and recognition process. Before removing the low frequency background image is sharpened it minimizes the noise from the image. Histograms are mapped to reduce the gap between inferior and dominant color channels after this wavelet fusion is applied. The result of the proposed is more effective and improves the image quality**. Erat, Ozan, et. al [7]** in this paper, the author works on the contrast enhancement for underwater images in maritime border protection. This type of method is used to capture the unlawful materials. It is mainly used to detect the capsized boat in the water. This method reduces the color cast and enhances the image contrast. The computation consumption is low in the proposed method. It provides high throughput and effective frame rate. **Qiao, Xi, et. al [8]** in this paper, the author proposed relative global histogram stretching for water image enhancement approach. This approach consists of two parts that are color correction and contrast correction. In contrast correction method RGB color space is used and redistributes each RGB channel histogram. These dynamic parameters are related to intensity distribution of original image and wavelength attenuation of different color underwater. To reduce the noise from the image bi-lateral filtering is used and enhances the local information of shallow water image.**Wang, Y. et. al [9]** in this paper, the author proposed a novel underwater image restoration method which is based on prior called adaptive attenuation-curve prior. This prior is based on the statistical distribution of pixel value. Pixels of the image are divided into clusters in RGB space. Power function is used to assign value to each cluster. Saturated constraints are used to reduce the noise and adjust three color channels. **Wang, N.**

et. al [10] underwater image restoration is done by using attenuation identification. In this work light propagation model is used as the transmission model. The proposed method is called as maximum attenuation identification. This method is used for deriving depth map from the degraded underwater images. This experiment is performed on three groups of images that are natural underwater scene, calibration model and color map model. **Codruta, O. et. al [11]** in this paper, the author proposed single-scale fusion which is used to merge the images. This method reduces the MSF only at single level and MSF is used at minimal loss of information. Underwater image enhancement is divided into two methods that are image dehazing and image color restoration. This paper presented a detailed survey of the approaches and methods that used in underwater image enhancement and summary on underwater image processing methods.Chaubey, **Ankit, et. al [12]** a hybrid approach DWT-DCLAHE method is used to enhance the low contrast underwater images. In this work DWT is applied on the RGB image on LL band. Then apply the DCLAHE on the luminance part of LL band. After this process convert the YCBCR to RGB format. DWT is used to merge the modified band. The result of the approach is applied to peak signal noise ratio (PSNR), entropy and time execution. This algorithm is compared with existing algorithm and it performs better. **Li Xiu, et. al [13]** in this paper, the author proposed image enhancement by using dark channel prior and luminous adjustment. Color distortion in images occurred due to absorption degrees changes according to light wavelength. The result of the paper shows the improved global contrast and better image preservation**. Yujie, L. et. al [14]** introduced image de-scattering and classification by using deep neural network. This method is based on the color correction which enhances the high turbidity in the underwater images. This method removes the scatter from the images and preserves the color. It also proposed quality assessment index for performance comparison. This index combines the color distance index and SSIM index. The classification is done by using support vector machine and convolution neural network.

III. THE PROPOSED METHOD

3.1Proposed Methodology

Step 1: Input the Image.
Step 2: Pre-processed the image and extract features.
Step 3: Apply convolution Process on image.
Step 4: After convolution low dimension matrix is produced.
Step 5: Initialize the grey wolf algorithm.
Step 6: Search local and global best by water cycle.
Step 7: Check the output is optimized or not if optimized the go to Step 8 otherwise go to step 4.
Step 8: Calculate the total variation.
Step 9: Analyze the PSNR and MSE of the Image.

3.2 Proposed methodology: Flowchart

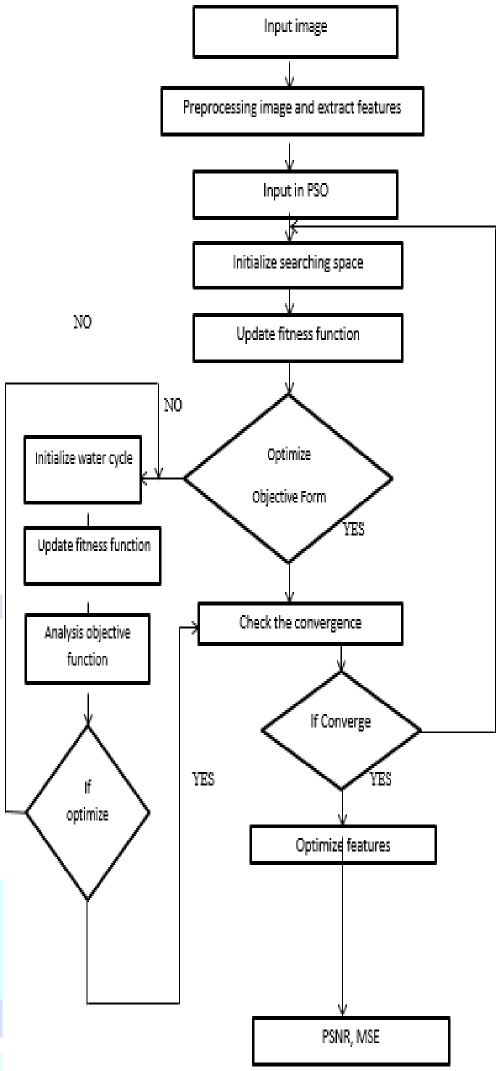

Figure 3.1: Proposed Flowchart

3.3 Algorithm Used

Particle Swarm Optimization: PSO stands for particle swarm optimization**.** PSO is a stochastic optimization algorithm which is based on the behaviour of birds. It works similar to the genetic algorithm. In PSO is initialized with a group of random particles. In every iteration , each particle is updated by the two "best" values. The first best solution shows the fitness of the particles and this called as pbest. The second best value is tracked by the optimizer is the best value. This value is called as global best (gbest).When a particle takes part of the population as its topological neighbours; the best value is a local best and is called best.

Step 1: Input the images.
Step 2: Pre-processing of the images.
Step 3: Convolution of the images for low dimension images.
Step 4: For optimization input in the PSO model.
Step 5: Apply the loop in PSO model. for each particle n in S do
Step6 : for each dimension d in D do
Step7: //initialize each particle's position and velocity
Step8: $y_{p,q} = \boldsymbol{Rnd}(\boldsymbol{y_{max}}, \boldsymbol{y}_{\min})$
Step9: $\boldsymbol{z_{p,q}} = \boldsymbol{Rnd}(-\boldsymbol{z_{max}}/3, \boldsymbol{z_{max}}/3)$

Step10: end for

Step11: //initialize particle's best position and velocity

$z_p(l+1) = z_p(l) + \gamma 1_n(p_n - y_n(l)) + \gamma_{2n}(G - y_n(l))$

New velocity

$y_n(l+1) = y_n(l) + y_n(l+1)$

Where

p denotes the particle index

l denotes discrete time index

z_p denotes velocity of n^{th} particle

y_p denotes position of n^{th} particle

p_n denotes best position found by n^{th} particle(personal best)

J denotes best position found by swarm(global best, best of personal bests)

$J_{(1,2)i}$- random number on the interval[0,1]applied to the n^{th} particle

Step12 : $pb_n = y_p$

// update global best position

Step13: if $f(pb_n) < f(gb)$

Step 14: $gb = pb_n$

Step15: end if

end for

Step16: Find the value of Total Variation.

Step17: Analysis of PSNR and MSE.

IV. RESULT ANALYSIS

4.1 Effect on Image

4.2 Previous results

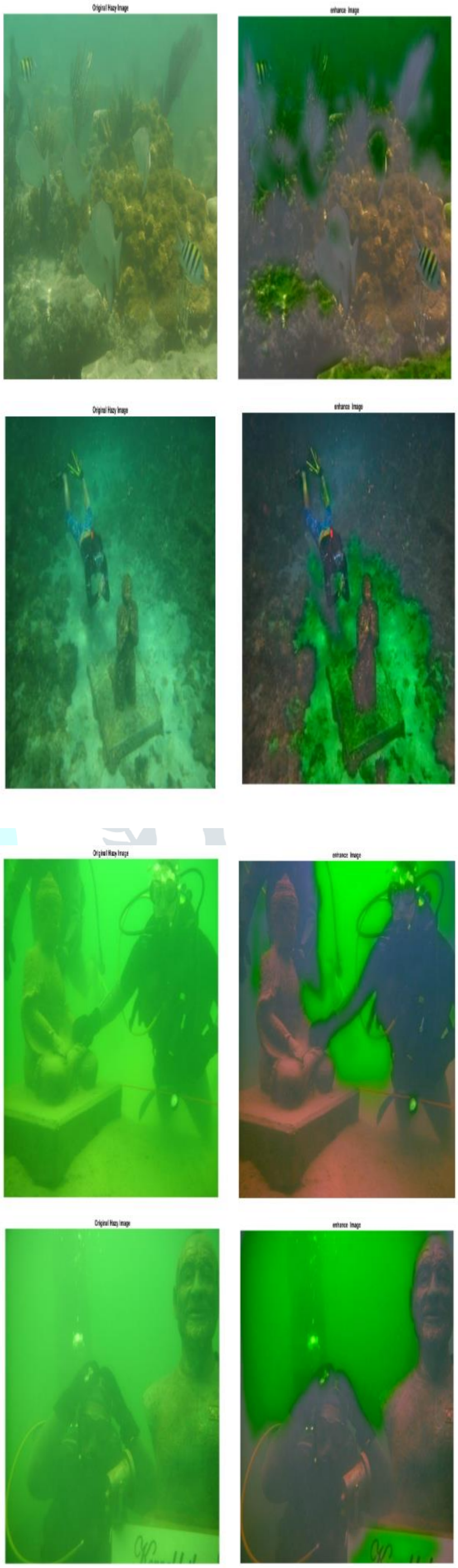

Figure 4.1: Existing approach before and after images

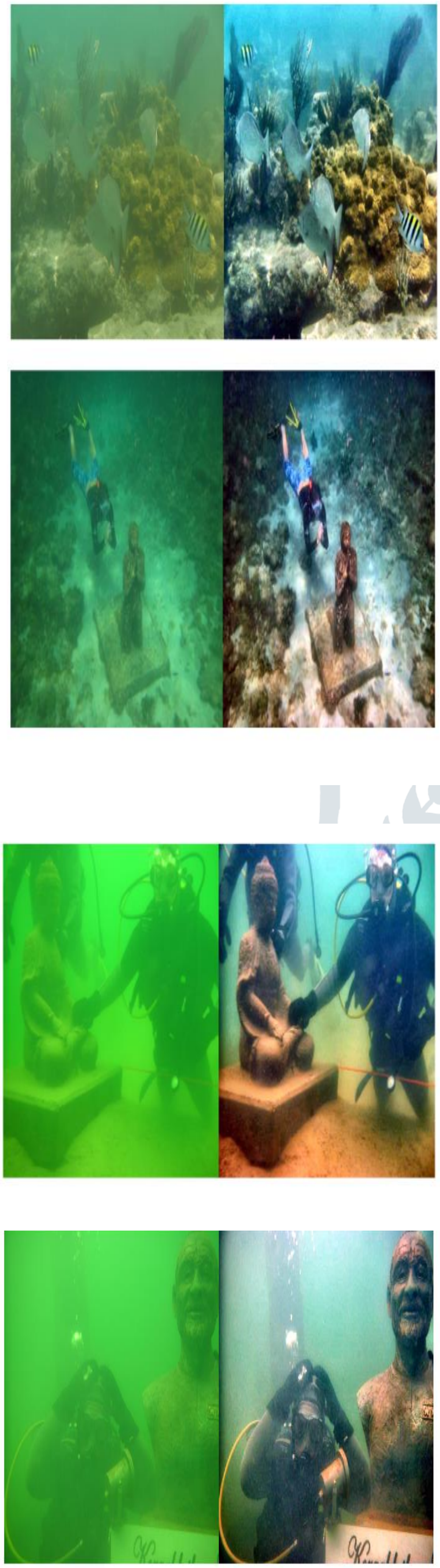

Figure 4.2: Proposed Approach before and after images

4.3 Previous Results

Table 4.1: PSNR and MSE of previous results

Image No.	PSNR	MSE
Image 1	32.13	45.13
Image 2	30.23	52.23
Image 3	29.13	61.23
Image 4	20.45	70.45
Image 5	20.13	71.65

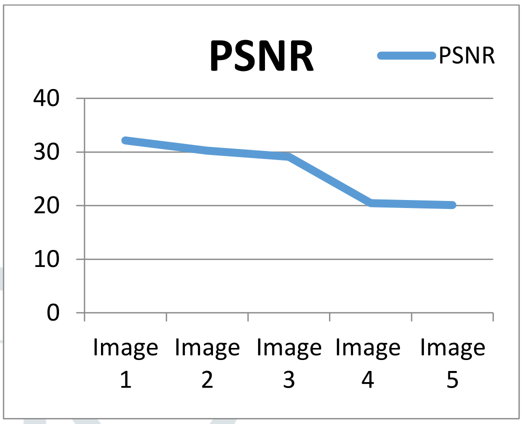

Figure 4.3: Graph of PSNR in previous results

Figure 4.3 depicts the PSNR value of the five images in the existing approach. In this Image 1 has PSNR value 32.13 which is highest and image 5 has 20.13 which is lowest among the all images which are undergone in this experiment.

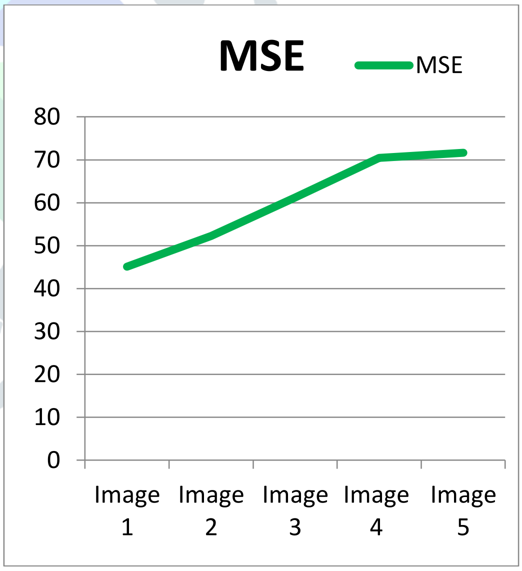

Figure 4.4: Graph of MSE in previous results

Figure 4.4 depicts the MSE value of the five images in the existing approach. In this Image 5 has MSE value 71.65 which is highest and image 1 has 45.13 which is lowest among the all images which are undergone in this experiment.

Figure 4.5: Graph of PSNR and MSE of previous results

Figure 4.5 depicts the PSNR and MSE value of the five images in existing approach. This graph shows two lines in which red line indicates the MSE value of images and blue line indicates the PSNR of the images. The position of lines changes according to the variation in the results.

4.4 Proposed Method Results

Table 4.2: PSNR and MSE of proposed method

Image No.	PSNR	MSE
Image 1	39.13	30.45
Image 2	32.13	32.13
Image 3	30.13	50.13
Image 4	26.13	57.23
Image 5	25.25	58.23

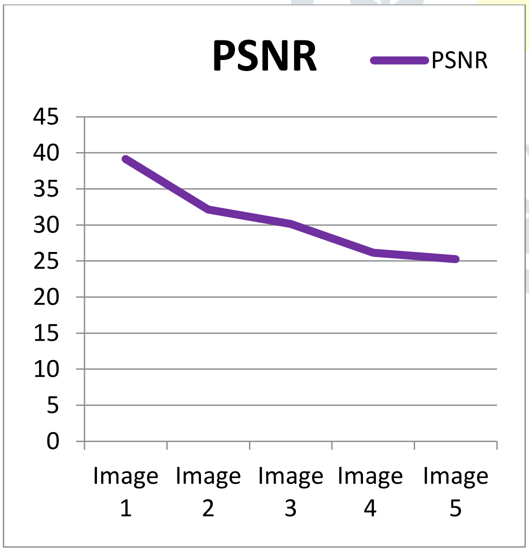

Figure 4.6: Graph of PSNR of proposed results

Figure 4.6 depicts the PSNR value of the five images in the proposed approach. In this Image 1 has PSNR value 39.13 which is highest and image 5 has 25.25 which is lowest among the all images which are undergone in this experiment.

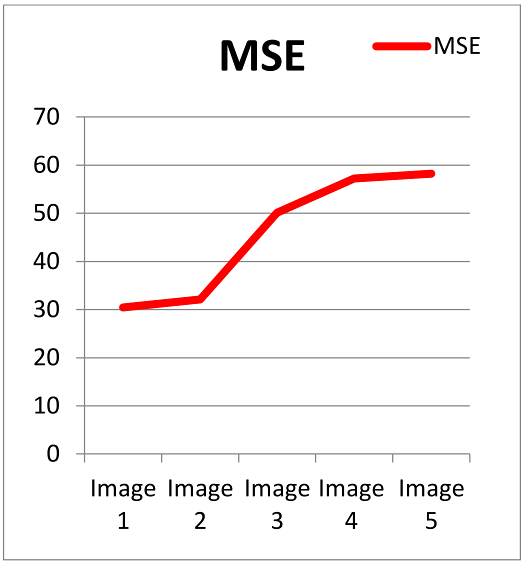

Figure 4.7: Graph of MSE of proposed results

Figure 4.7 depicts the MSE value of the five images in the proposed approach. In this Image 5 has MSE value 58.23 which is highest and image 1 has 30.45 which is lowest among the all images which are undergone in this experiment.

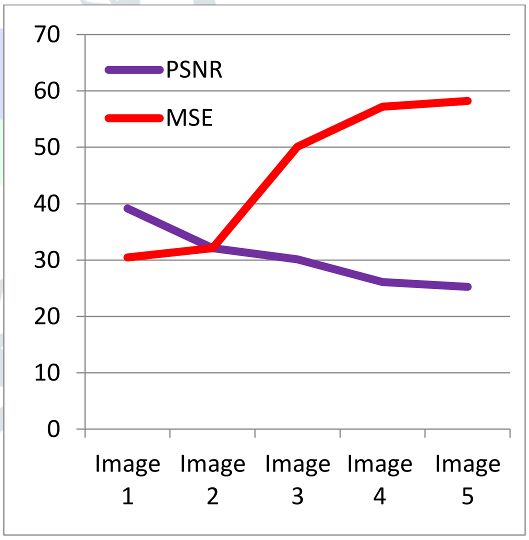

Figure 4.8 : Graph of PSNR and MSE of proposed method

Figure 4.8 demonstrate the value of PSNR and MSE of five images in the proposed method. This graph shows two lines in which red line indicates the MSE value of images and blue line indicates the PSNR of the images. The position of lines changes according to the variation in the results.

Table 4.3: Comparison of existing and proposed results

Image No.	PSNR Existing	PSNR Proposed	MSE Existing	MSE
Image 1	32.13	39.13	45.13	30.45
Image 2	30.23	32.13	52.23	32.13
Image 3	29.13	30.13	61.23	50.13
Image 4	20.45	26.13	70.45	57.23
Image 5	20.13	25.25	71.65	58.23

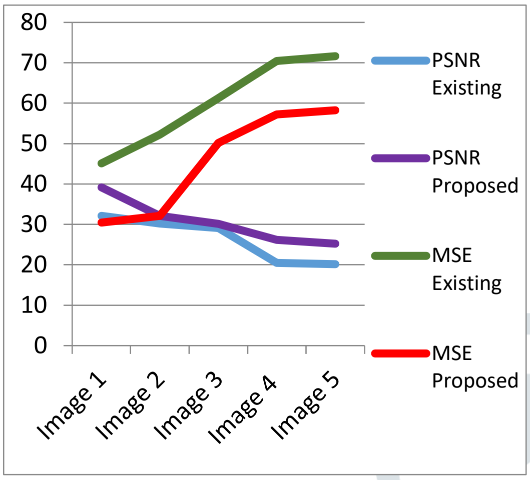

Figure 4.9: Graph of PSNR and MSE of proposed method and existing method.

Figure 4.9 depicts the comparison between the PSNR and MSE of the proposed work and existing work. In this blue line shows the existing PSNR, red line shows the PSNR proposed, green line shows the MSE existing and purple line represents the MSE proposed of the images.

IV CONCLUSION

This thesis has presented a novel approach for stitching images acquired underwater which is able to tackle the problems that arise when using common image stitching methods on underwater images. In the first step, dehazing is used to improve the aesthetic quality of images as well as to improve data quality for the task of feature detection. Guided image filtering is used to speed up the process of dehazing the images. Then SIFT is used to find and match features between images and a single homography per image was used to perform alignment. In the next step, a graph cuts-based seam cutting method in the image gradient domain is used to find the optimal cut between two images in order to reduce visible seams in the overlapped regions. While producing an image with no overlaps using seam cutting, we use linear blending to reduce colour discontinuities that may still exist. A novel idea proposed in this method is to use colour normalization to transform images into the same colour space to make the stitching result even more “seamless”.

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