ENHANCING UNDERWATER IMAGES BY LEVERAGING TRANSMISSION MAP,WHITE BALANCE AND MULTI-SCALE FUSION

PROJECT REPORT

Submitted by

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Under the guidance of
Prof. Reena Mary George

Thangal Kunju Musaliar College of Engineering
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DECLARATION

I,undersigned hereby declare that the project report on **"Enhancing underwater image by leveraging Transmission map, White balance and Multi-scale fusion"**, submitted for partial fulfillment of the requirements for the award of the degree of Master of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under the supervision of **Prof. Reena Mary George**, Assistant Professor of the Computer Science and Engineering Department, TKMCE. This submission represents our ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed as the basis for the award of any degree, diploma or similar title of any other University.

Kollam AKHILA R
10/07/2023

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C E R T I F I C A T E

This is to certify that this report titled ***Enhancing underwater images by leveraging Transmission map, White balance and Multi-scale fusion*** is a bonafide record of the **Project** presented by **AKHILA R(TKM21CSCE01)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **M.Tech** in **Computer Science & Engineering** in **APJ Abdul Kalam Technological University** .

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Abstract

Due to the medium's scattering and absorption, underwater image captures are prone to colour distortion, detail loss, and contrast reduction. The article provides a technique for enhancing underwater photography quality that doesn't require any special software,more than the native single image.The three techniques are used here for enhancing underwater image include Transmission map, an enhanced white-balancing method,and multiscale image fusion method .A guidance filter is adapted to refine the estimated transmission map depth.The suggested technique increases the underwater object's visibility and restores quality image. The white balancing method is to remove the color distoration from underwater image,it uses 5 channel compensated approaches,these 5 channels are white balanced using gray world algorithm.In white-balancing method, the Underwater Colour Image Quality Evaluation (UCIQE) and the Underwater Image Quality Measure (UIQM) are added together to determine the best color-compensated method. The gamma-correction process is used to create numerous underexposure versions from a single underwater images. Then, in the well-known multi-scale fusing approach , suggest blending "chrominance","luminance",and "saliency" as three weights. The visual quality of an image is predominantly influenced by these weights, aiming to generate a fusion result with improved visual appeal.Through validation with a wide range of qualitative and quantitative evaluations ,has been able to demonstrate that images enhanced by our strategy have superior visual quality than other cutting-edge underwater dehazing procedures.

Keywords : *Transmission map*, *white balance*, *multiscale fusion*, *quantitative evaluation.*

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List of Abbreviations

UCIQE .... Underwater Color Image Quality Evaluation
UIQM .... Underwater Image Quality Measure
UISM .... Underwater image sharpness measure
UICM .... Underwater image colorfulness measure
UIConM .... Underwater image contrast measure
PCQI .... Patch-based contrast quality index
AG .... Average Gradient

Chapter 1

Introduction

Recently, the use and exploitation of different marine animals and resources have become a popular topic due to the various professional duties and scientific discoveries enabled by underwater imagery, such as monitoring underwater artificial facilities, detecting underwater items, finding marine life, and managing underwater vehicles. However, images that are directly taken from an underwater environment always experience significant degradation, such as unwanted colour cast, reduced contrast, and detail loss brought on by light scattering and absorption, which severely restricts the acquisition of the image's available information.Acquiring precise and clear photographs is a crucial step in assisting scientists in understanding the underwater environment.

To increase the visibility of underwater photographs, a variety of methods have been suggested. For instance, several researchers suggested using polarization-based techniques or specialised hardware devices to improve deteriorated photos. Despite the tremendous performance achieved with these technologies, there were still certain restrictions. To further enhance the visual quality of the scenario, some researchers suggested using multi-images-based fusion techniques . However, it is impracticable for regular users to do the exceedingly challenging process required for underwater imaging to acquire numerous versions of a single scene.

Researchers focused more on developing single picture dehazing techniques as their research progressed because they don't require any additional hardware or complicated operations. Underwater picture enhancement based on single image can be categorized as underwater image enhancement, underwater image restoration, and data-driven methods for underwater single image dehazing . The approaches for underwater picture restoration constantly need more background information to rebuild the damaged image. Recent data-driven method proposals typically have significant hardware and training dataset requirements. These techniques are frequently inoperable in routine underwater imaging situations due to their drawbacks.

A novel method based on single image dehazing which utilizes a ”Three step” strategy involving transmission map,white balancing and multiscale fusion is proposed here.The first step is the estimation of transmission map depth,which is the difference between the maximum and minimum intensity priors.Further refinement of transmission map depth is done using guidance filter. The guidance filter is used to maintain the visual information by preserving the edges, smoothing the texture and without any artifacts. The suggested technique increases the underwater object's visibility and restores quality image. In the second step channel compensation is done via five approaches : viz. compensation of red channel from green channel, red from blue, red from green and blue, red and blue from green, red and green from blue.After that white balancing using gray world approach is done on these five channels.The purpose of the white balancing method is to remove the color distoration from underwater image.

To evaluate the visual quality of an image, the evaluation indicators used here are Underwater Color Image Quality Evaluation (UCIQE) and Underwater Image Quality Measure(UIQM).Therefore, analysed five channel-compensated, white balanced images using UIQM and UCIQE, respectively, and the two images which gives the maximum values for our evaluation indicators are selected For each of the images with maximum UCIQE and maximum UIQM ,10 images are generated by varying alpha values.From these 20 images found the two images having maximum UCIQE and UIQM , these two images are combined to form a single image.

The next step is to enhance the contrast and recover the details in the image.Various exposures of the same scene can reveal details more clearly in areas with different brightness. Details in the bright portions of a short-exposure image are well preserved, but details in the dark sections are rapidly fading. In the meantime in a totally a long-exposure shot, the reverse behaviour is visible.Therefore, researchers suggested combining multiple exposure versions to produce images that effectively communicate information in both dark and light areas.But in the underwater environment acquiring different exposure version of a single scene is difficult.Therefore, gamma-correction is applied on the image obtained,which creates numerous underexposed versions from a single underwater image. After that, swap out the weight-maps for the multi-scale fusion technique to improve the visual quality of underwater photographs.The three weights used here as "Luminance","Chrominance" and "Saliency",gaussian and laplacian pyramids are generated from these weights. The multifusion strategy is applied on these weight maps, aims to recovering details.

The major contribution of this research as follows.

1) For improving the visual quality of an underwater image the transmission depth map is refined using guidance filter and the rolling guidance filter ,then white balancing and multiple-exposure strategy is used .

2) Refinement of transmission map depth is done using guidance filter. These filters maintain the visual information, including edge preservation, texture smoothing, and results without artefacts. The suggested procedure raises the visibility and restores the single underwater image's quality.

3) The non-reference quantitative evaluations are used to produce the ideal white-balancing method on underwater photos.The white balancing approach is used to remove color distoration from underwater images.

4)The substituted weights are incorporated into the well-liked multi-scale fusing method to improve underwater photographs with greater visual quality than certain current multi-exposure fusion techniques.

Chapter 2

Related Works

Underwater photographs always experience the effects of light scattering and absorption, which is the major distinction between underwater images and ordinary images. Both the scattering and the absorption processes can lead to a loss of detail and a decrease in contrast [1]. Since light with shorter wavelengths may penetrate deeper depths than light with longer wavelengths, the absorption process is likewise directly tied to light wavelength, giving underwater photographs a distinctive bluish or greenish tone. In water, red light degrades significantly after 5–6 m, followed by orange, yellow, green, and blue light. This phenomenon is known as selective attenuation.

The three main branches of the mainstream of underwater single image dehazing approaches are data-driven methods, methods based on prior knowledge, and methods based on deep learning, as well as improvement methods based on fusion or spatial/frequency domain transformations.The Dark Channel Prior (DCP) technique is the most emblematic of the underwater single picture restoration branch.He et al.'s approach [2], which was initially used to dehaze fogged pictures, was proposed. DCP assumes that one colour channel's radiance has very low intensities, as a result, refers to areas with weak transmission as the ones with a high colour minimum value. It work effectively to dehaze underwater photographs but less so to defog atmospheric images. Then, various algorithms produced DCP suggested dehazing underwater photos. To increase the visibility of underwater photos, Chiang et al. [3] suggested combining the conventional DCP and a color-compensation approach. Although the method might boost and compensate for wavelength attenuation
A strategy for effective enhancement based on histogram distribution was proposed by Li et al.[4],Prior and minimal information loss could improve underwater image contrast and brightness. Yang et al.'s [5] recent proposal for a reflection-decomposition-based method.The under-water image can be

reconstructed using the transmission map estimation method. The visual quality of underwater photographs was in fact improved by these techniques. However, this methodical offshoot often requires a great deal of additional background knowledge, which the majority of common consumers seldom possess.Greater accomplishments have been made in recent years, but they call for a lot of additional background knowledge.

In recent years,progressively better developments in image segmentation [6] and super resolution [7] and Deep learning algorithms have been used to create object detection [8]. Dehazing underwater pictures entails,Deep-learning based methodologies also contributed significantly [9]–[12]. The well-known Convo-lutional Neural Network (CNN), which improves brightness, was proposed by Wang et al.[11],but results in over-red-compensated underwater photos due to the input's brightness and contrast.Li et al.'s [12] suggestion was submerged picture improvement UWCNN, an underwater scene-based convolutional neural network.It enhances underwater image visibility but has a significant training data requirement. In conclusion, deep learning-based algorithms always require extensive training time and have complex network architecture. Their Enhancing effects are solely dependent on the calibre of the challengingly built training set.

An algorithm designed specifically for enhancing underwater photos by Galdran et al. [13] has shown promising results in addressing low contrast and chromatic aberration. The flaw is that some photos will exhibit variable degrees of red supersaturation, giving the overall appearance of a reddish image. In order to tackle colour correction and detail enhancement, a method for underwater image enhancement should be developed.

The image formation model-based (IFM-based) method and the image formation model-free (IFM-free) method can be used to categorize existing underwater picture improvement techniques [14]. The IFM-based method refers to the mathematical modeling of the underwater image deterioration process, which involves estimating the model parameters and reversing the degradation process to obtain a clear underwater image. Specifically, the dark channel prior (DCP) [15], a defog method originally designed for outdoor images, plays a crucial role. According to this method, photographs captured on a clear day tend to exhibit pixels with extremely low intensities (close to zero) in at least one color channel.

Several researchers have modified the DCP algorithm to adapt it for underwater scenarios. For instance, Chiang et al. [16] proposed a combination of the DCP algorithm with a wavelength-dependent compensation technique for defogging and color correction. Galdran et al. [17] introduced a method that utilizes red channel compensation to recover contrast lost in underwater images, leveraging the characteristic of red light attenuating the fastest during underwater propagation. Lu et al. [18] proposed a novel mathematical model for underwater images and employed wavelength compensation to restore them.

The IFM-free method focuses on enhancing the contrast and color of the image by redistributing pixel intensity, without relying on the image formation model. Image fusion is an effective strategy for underwater image enhancement. Ancuti et al. [19] introduced a fusion-based approach that generates two different versions of the input images. The approach then determines four weights based on Laplacian contrast, local contrast, saliency, and exposure. Finally, a multi-scale fusion strategy is applied to combine the two fused images using the defined weights, resulting in an enhanced image with improved global contrast and detailed information. Ancuti et al. [19] further improved their fusion method by proposing a new red channel compensation technique and updating the weight calculation method. These advancements resulted in images displaying enhanced dark areas, improved overall contrast, and sharpened edges.

The techniques for improving underwater photographs that rely on spatial/frequency domain modifications or fusion strategies improve them by increasing contrast, enhancing details, and improving visual perception [20]. The well-known techniques, which are widely regarded as conventional contrast-enhancement techniques and include Histogram Equalisation (HE) [21], Contrast Limited Adaptive Histogram (CLAHE) [20], and Generalised Unsharp Masking (GUM) [23], never succeed in dehazing underwater photos. Later, fusion-based approaches drew the attention of an increasing number of researchers. Fusion-based techniques primarily adjust colour, recover details, and boost contrast to restore the visual quality of deteriorated photos.In addition to making significant contributions to dehazing underwater photos, they consistently adhere to the Laplacian and Gaussian Pyramid techniques. The most effective techniques are those suggested by Ancuti et al. [18] and Ancuti et al. [19]. In [24], scientists suggested reconstructing the underwater image by combining a color-corrected version with a contrast-enhanced version using four predefined weights. When inputs are affected by artificial light, however, the improved results do not perform well. The approach [25] suggested a multi-scale fusion strategy that fuses a gamma-corrected version from their white-balanced image and a sharpened version from the same image.In single channel compensated approach, included both white balancing and multifusion strategy.

Chapter 3

Proposed method

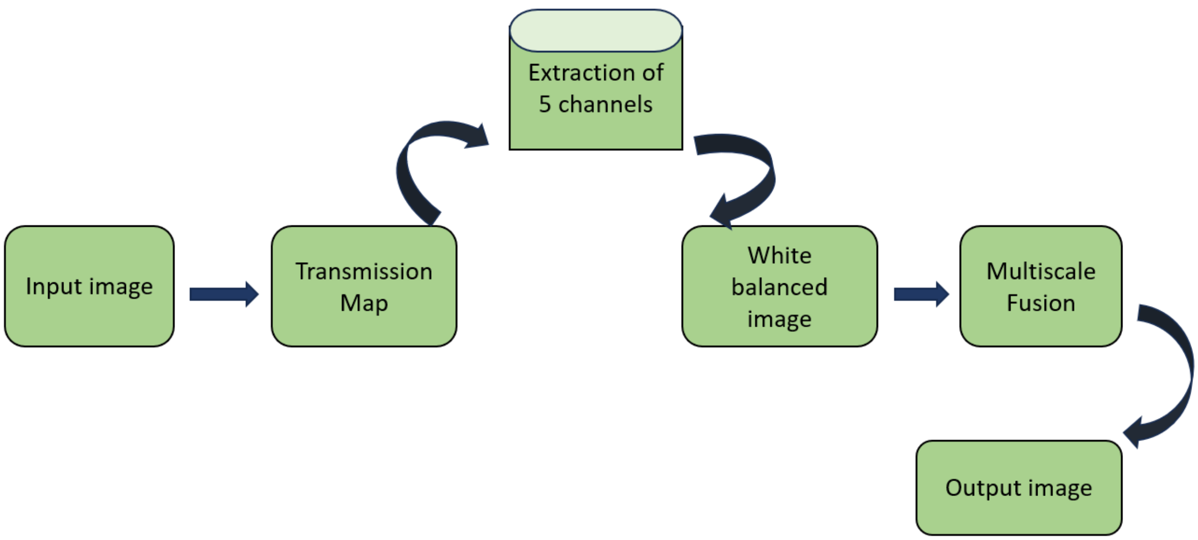

Figure 3.1: Architecture of proposed method.

The underwater single image improvement includes transmission map, enhanced white-balancing technique and multiple underexposure fusion mechanism. Transmission map can be used to enhance the visibility and recover the details in the underwater image. It uses a guided filter to preserve the edges,texture smoothening etc. By combining the well-known Grey World assumption with the best color-compensated method, obtain an ideal white-balanced version,where intially set the alpha value as 1 for each approach.The best color-compensated strategy in our white-balancing method is decided by the sum of two widely accepted objective evaluation indicators, UCIQE and UIQM .Then the gamma correction process is employed to create five underexposure versions from the white-balanced input in multiple underexposure image fusion technique. Then, in the well-known multi-scale fusing technique, propose employing ”luminance,” ”chrominanace,” and ”saliency” as three weights.By combining these three methods, an enhanced underwater image is obtained.

3.1 Transmission map Estimation

The portion of the light that is not dispersed and reaches the camera is described by the transmission map. As a continuous function of depth, the map so represents the scene's depth information.The transmission map depth is calculated by using Dark channel prior technique.By exploiting the dark channel statistics, it estimates the haze-free transmission map, which represents the amount of light reaching the camera from the scene.The dark channel is calculated by finding the minimum intensity value across a local window for each pixel in the underwater image. The dark channel highlights the regions with minimal light attenuation and provides valuable information about the scene's haze-free areas. In order to preserve the edges, texture smoothing, and artifact-free outcomes, guidance filter refine the transmission map.The transmission map, denoted as "T(x, y)", represents the proportion of light that reaches the camera from a scene point at coordinates (x, y) relative to the total amount of light emitted by the scene point. The transmission map is typically normalized between 0 and 1, where 0 represents complete opacity (no light reaches the camera) and 1 represents complete transparency.

The equation for the transmission map is given by:

$$T(x, y) = 1 - w \cdot \min(R(x, y), G(x, y), B(x, y)) \tag{1}$$

where $T(x, y)$ is the transmission map at pixel (x, y), $R(x, y)$, $G(x, y)$, and $B(x, y)$ are the color values of the corresponding red, green, and blue channels at pixel (x, y), and w is a parameter controlling the strength of the haze removal.

3.1.1 Transmission map refinement using guided filter

Visual details like edges and textures can be seen in the underwater photographs. The visual information must be cleaned of any unhelpful infor-

mation, such as noise, artifacts, and halo effects. Such uninformative data lead to a decline in the image quality. The guided filter preserve the visual information by producing outputs with smoothed textures, preserved edges, and no artifacts.
The equation for guidance filter is given by:

$$\hat{I}(p) = \frac{1}{\hat{W}(p)} \sum_{q\in\Omega} I(q) \cdot \mathrm{sim}(p, q) \tag{2}$$

where, I(q) is the input image intensity at pixel P,sim(p,q) is the similarity measure between pixels p and q.The guided filter [22] also maintains edges in the input image , while refining the predicted transmission map . In this study, the estimated transmission map T(x,y) is approximated using the colour guidance .

3.2 Underwater whitebalancing Method

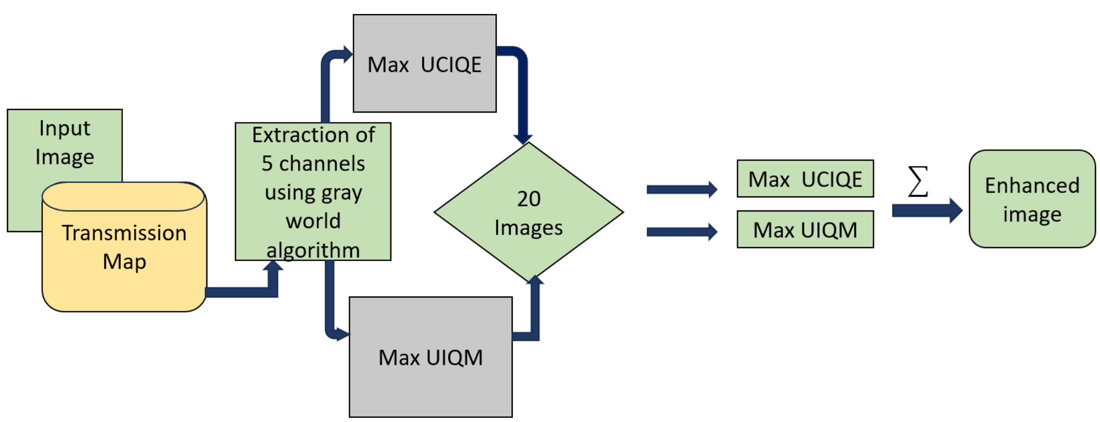

Figure 3.2: White Balancing method.

Scholars have developed white-balancing methods to address the color cast caused by the depth of water in underwater environments. However, due to low contrast and undersaturation in underwater imaging, it is challenging to determine which channels, apart from the red channel, should be compensated. To overcome this, a practical approach is needed to select the optimal channel-compensated method.After the estimation of transmission map depth,white balancing is performed to enhance the image.Taking inspiration from Kumar and Bhandari [23], who proposed compensating the color channels in twelve different approaches, focus on five specific channel-compensated approaches.The constant parameter alpha, which controls the compensation strength, varies within the range of [0, 1].Using Gray world algorithm,white balance these 5 channel compensated approches, where intially set the alpha value as 1 for each approach. These approaches include compensating the red channel from the green channel, compensating the red channel from the blue channel, compensating the red channel from both the green and blue channels, and compensating the red and blue channels from the green channel.

The following are the 5 compensation approaches:

- Compensation of red channel from green channel:

$$I_{\text{re}}(x) = r + \alpha \cdot (\text{avg}_g - \text{avg}_r) \cdot (1 - r) \cdot g \tag{3}$$

- Compensation of red channel from blue channel:

$$I_{\text{re}}(x) = r + \alpha \cdot (\text{avg}_b - \text{avg}_r) \cdot (1 - r) \cdot b \tag{4}$$

- Compensation of red channel from green and blue channel:

$$I_{\text{re}}(x) = r + \frac{\alpha}{2} \cdot (\text{avg}_g - \text{avg}_r) \cdot (1 - r) \cdot g + \frac{\alpha}{2} \cdot (\text{avg}_b - \text{avg}_r) \cdot (1 - r) \cdot b \tag{5}$$

- Compensation of red and blue channel from green channel:

$$\begin{aligned} I_{re}(x) &= I_r(x) + \alpha \cdot (\bar{I}_g - \bar{I}_r) \cdot (1 - I_r(x)) \cdot I_g(x) \\ I_{be}(x) &= I_b(x) + \alpha \cdot (\bar{I}_g - \bar{I}_b) \cdot (1 - I_b(x)) \cdot I_g(x) \end{aligned} \tag{6}$$

- Compensation of red and green channel from blue channel:

$$\begin{aligned} I_{re}(x) &= I_r(x) + \alpha \cdot (\bar{I}_b - \bar{I}_r) \cdot (1 - I_r(x)) \cdot I_b(x) \\ I_{be}(x) &= I_b(x) + \alpha \cdot (\bar{I}_b - \bar{I}_g) \cdot (1 - I_b(x)) \cdot I_b(x) \end{aligned} \tag{7}$$

The intensity of the compensated channels at pixel location x, denoted by $I_{\mathrm{re}}(x)$, $I_{\mathrm{ge}}(x)$, and $I_{\mathrm{be}}(x)$.Similarly, $I_r(x)$, $I_g(x)$, and $I_b(x)$ represent the intensity of the original channels at pixel location x, with each value normalized to the interval [0, 1] relative to the upper limit of the dynamic range. The average mean-values of the red, green, and blue channels are denoted by $\overline{I_r}$, $\overline{I_g}$, and $\overline{I_b}$, respectively.

Then evaluate the five white-balanced versions using the UCIQE (Underwater Color Image Quality Evaluation) and UIQM (Underwater Image Quality Measure) metrics. The UCIQE metric to evaluate the quality of the white-balanced versions, which is calculated as follows:

$$UCIQE = c1 \cdot \sigma_c + c2 \cdot \mathrm{conl} + c3 \cdot \mu_s \tag{8}$$

where σ_c represents the standard deviation of the image chromaticity, conl denotes the contrast of the image brightness, and μ_s signifies the mean value of the image saturation. The weighted coefficients $c1$, $c2$, and $c3$ are set to 0.4680, 0.2745, and 0.2576, respectively. A higher value of UCIQE indicates better quality for the underwater image.The UIQM is computed using the following formula:

$$UIQM = c1 \cdot UICM + c2 \cdot UISM + c3 \cdot UIConM \tag{9}$$

where UICM represents the underwater image colorfulness measure, UISM denotes the underwater image sharpness measure, and UIConM signifies the underwater image contrast measure. The weighted coefficients $c1$, $c2$, and $c3$ are generally set to 0.0282, 0.2953, and 3.5753, respectively. A higher value of UIQM indicates better quality for the underwater image.

	UCIQE	UIQM
Image 1	0.472	4.125
Image 2	0.501	5.113
Image 3	0.442	4.120
Image 4	0.411	5.012
Image 5	0.534	5.138

Table 3.2: UCIQE and UIQM values of 5 underwater images

Therefore, the maximum value of UCIQE or UIQM should be present in the ideal white-balanced version. A whitebalanced image is also extremely likely to have an optimal value for the other quantitative assessment metric at the same time that it has an optimal value for the first, adjust the value of the constant parameter in [0, 1].It create a total of 20 white-balanced pictures.From the set of 20 white-balanced images, we evaluate their quality using UCIQE and UIQM metrics.

$$\begin{aligned} IQA(m) &= UCIQE(m) + UIQM(m) \\ UCIQE(m) &= \frac{UCIQE(m) - \min(UCIQE)}{\max(UCIQE) - \min(UCIQE)} \times 100 \\ UIQM(m) &= \frac{UIQM(m) - \min(UIQM)}{\max(UIQM) - \min(UIQM)} \times 100 \end{aligned} \quad (10)$$

Here, m represents the index of the white-balanced version ranging from 1 to 20. UCIQE(m) is the UCIQE value for the mth version expressed as a percentage, and UIQM(m) is the UIQM value for the mth version expressed as a percentage. The IQA(m) represents the composite metric obtained by adding UCIQE(m) and UIQM(m). The m value with the highest IQA determines the optimal white-balancing method and the optimal value of .After correcting the colour distortion,then to increase contrast and recovery details.

3.3 Multiple underexposure fusion

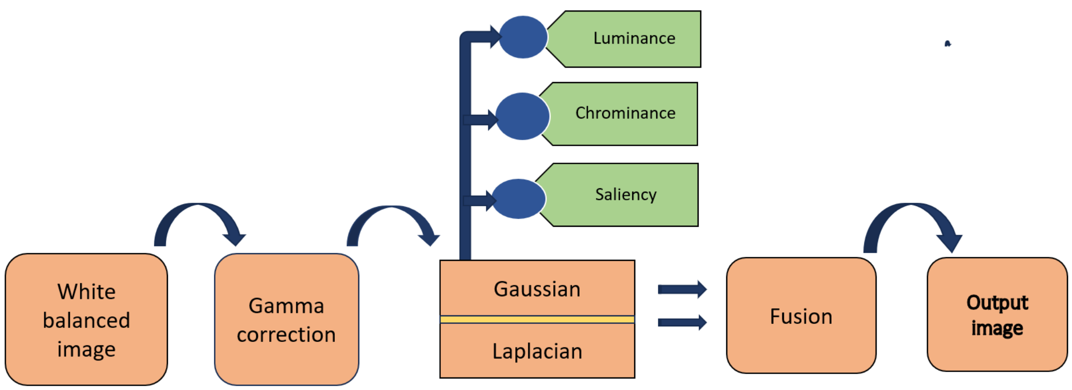

Figure 3.3: Structure of Multi-scale Fusion method.

To improve contrast and restore details , use a spatially-varying enhancement technique.Images' global contrast is typically increased or decreased using the gamma-correction process.Alternative values , can be set to produce underexposure versions. Even if reducing exposure reduces brightness of the image, underwater photographs can nevertheless recover details well to the fusion of several underexposed versions. It involves applying a non-linear transformation to the pixel values in order to achieve desired brightness or contrast enhancements.The gamma correction is performed on the enhanced images obtained from the white balanced method.

In gamma correction, the pixel values are typically scaled from the original linear space (with values ranging from 0 to 1) to a non-linear space using a power law function. The power law function is defined as:

$$V_{\text{out}} = V_{\text{in}}^{\gamma}$$

where V_{in} is the input pixel value, V_{out} is the output pixel value, and γ is the gamma value. The gamma value determines the shape of the transformation curve.The gamma value of 1 corresponds to no correction, resulting in a linear transformation. The effects of gamma correction with different gamma values ranging from 1 to 5. For each gamma value, explain how it affects the image's overall brightness, contrast, and visual appearance.The gamma corrected images then undergoes through multiscale fusion strategy,where this strategy contain three weights "Luminanace","Chrominance" and "Saliency".

3.3.1 Weights of Fusion strategy

Based on the studies [24] and [25], a source image is defined with three color-channel components. This allows for the calculation of weights in a multi-scale fusing scheme for each channel. Furthermore, the visual quality of an image is predominantly influenced by its luminance, chrominance, and saliency . To enhance the visual quality, establish weights based on these three characteristics, aiming to generate a fusion result with improved visual appeal.A weight graph can be used to emphasise the resultant pixels with high weight values. The Luminance, saliency, and chrominance properties of the image are used for the weight image selection.

- Saliency

The saliency map, plays a crucial role in highlighting objects and regions that may lose their saliency in underwater scenes.To achieve this, utilize the regional contrast-based salient object detection algorithm introduced by Cheng [26].The equation for saliency map is represented as,

$$W_{\text{Sal}} = \sum_{i=1}^{N} D(I_p, I_i) \cdot H(I_i) \tag{11}$$

where,W_{Sal} represents the saliency weight,$D(I_p, I_i)$ is the color distance metric between pixels I_p and I_i,$H(I_i)$ is the saliency map or weight associated with pixel I_i,N is the total number of pixels or image patches

- Luminance

The Laplacian contrast weight is a measure of global contrast in the image. It is computed by taking the absolute value of the Laplacian filter applied to each luminance channel. The Laplacian filter enhances the edges and textures in the image, thereby extending the perceived depth of field [27]. However, relying solely on the Laplacian contrast weight is insufficient for contrast restoration, as it cannot differentiate between ramp and flat regions.

- Chrominance

Chrominance refers to the color information or attributes of an image, representing the color components independent of brightness or luminance.The equation for chromatic map is represented as,

$$\text{chromaticmap} = \exp\left(-\frac{(\text{saturation} - \text{max\_saturation})^2}{2 \cdot \sigma^2}\right) \tag{12}$$

The equation calculates the chromatic map by exponentiating the negative square of the difference between the saturation and the maximum saturation, divided by twice the square of the sigma value.

The final weight for each underexposure is defined by taking the combined multiplicity of luminance,chrominance and saliency.The equation for finding the final weight as

$$W_k(x) = W_k(L) \cdot W_k(C) \cdot W_k(S) \tag{13}$$

where $w_k(L)$ is the weight of luminance,$w_k(C)$ is the weight of chrominance and $w_k(S)$is the weight of saliency.

3.3.2 Multi scale Fusion

The image fusion strategy has been extensively studied by numerous researchers, as mentioned in references [21] to [24]. Initially, a basic fusion approach known as ”Naive Fusion” was commonly used.

$$J(x) = \sum_{\kappa=1}^{K} \overline{W}_\kappa(x) E_\kappa(x) \tag{14}$$

where $J(x)$ represents the final result, K is the number of input versions $E_\kappa(x)$, and $W_\kappa(x)$ are the defined weights. The weights $W_\kappa(x)$ need to be normalized such that the sum of all weights is equal to 1, i.e., ensuring the intensity of $J(x)$ falls within a valid range. The final result $J(x)$ is obtained by multiplying each input version $E_\kappa(x)$ with its corresponding weight $W_\kappa(x)$.

The straightforward construction always caused unwanted halos to appear in the fusion product. A well-liked multi-scale fusing approach put forth by

Burt and Adelson [27] was offered to address this issue. To obtain the outcome additionally make use of the well-liked multi-scale fusing method.

The input images $E_k(x)$ and the normalized weights $W_k(x)$ are first decomposed using the Laplacian pyramid decomposition operation and the Gaussian pyramid decomposition operation, which results in the decomposition of $E(x)$ and $W(x)$ into the same number of levels. Then, at each level l, the Laplacian and Gaussian pyramids are combined to create the lth level of the Laplacian pyramid.

$$J_l(x) = \sum_{\kappa=1}^{K} G_l \odot \bar{W}_\kappa(x) + L_l\{E_\kappa(x)\} \tag{15}$$

where, G_l and L_l represent the l-th levels of the Gaussian and Laplacian pyramid decomposition operations, respectively. $J_l(x)$ denotes the fusion outcome at the l-th level. Finally, the fused level is reconstructed from the base to the top to obtain the final result $J(x)$.The visual quality of underwater photographs can be improved by using our multiple underexposure image fusion strategy, which efficiently recovers details and boosts contrast.

Chapter 4

Experimental Results

The experimental results aims to demonstrate the effectiveness of the proposed method . By conducting a wide range of analyses, including subjective evaluations and objective measurements, to assess the quality and performance of proposed approach. To provide conclusive evidence of the enhancement achieved by the method in terms of color correction, contrast enhancement, and overall image quality. The result should be evaluated using various metrics and visual comparisons to showcase the significant improvements in the method offers in comparison with the existing techniques.By analyzing the results side by side, aim to demonstrate how the proposed strategy outperforms other techniques in terms of visual quality, color accuracy, and overall image enhancement. The experimental results highlight the advancements and improvements achieved by the method, establishing its efficacy in the field of underwater image enhancement.

4.1 Dataset

The Underwater Image Enhancement Benchmark (UIEB) dataset is a valuable resource in the field of underwater image processing and enhancement, contain 890 raw underwater images. It provides researchers and practitioners with a diverse collection of underwater images captured under different environmental conditions and imaging scenarios. The dataset consists of a wide range of underwater scenes, including various water types, depths, and lighting conditions.UIEB dataset offers a comprehensive evaluation platform for assessing the performance of different underwater image enhancement algorithms. It enables researchers to compare and analyze the effectiveness of their proposed methods in terms of color correction, contrast enhancement, noise reduction, and overall image quality improvement . Its availability and diversity make it a valuable resource for advancing the state-of-the-art in underwater image processing. Researchers can leverage this dataset to develop novel algorithms, validate their results, and contribute to the improvement of image quality in underwater environments.

4.2 Strategy Evaluation

The undersea photographs' visual quality can be restored mostly by adjusting colour distortion, boosting contrast, and regaining details. The used pictures from our diving research and the UIEB database.UDCP [29], Ancuti et al. [30], L2UWE [2], Ancuti et al. [17], another Two-Step approach suggested by Fu et al. [29], and the deep-learning based method UWCNN [25] are some examples of other cutting-edge underwater picture dehazing approaches. The accompanying quantitative data from the three widely used performance indicators, UCIQE, UIQM, and PCQI.The 10 samples from the UIEB database provides the associated quantitative results obtained with three well-recognized performance metrics: UCIQE, UIQM, and PCQI .

Image	UCIQE	PCQI	UIQM
199_img_.png	0.573	0.973	4.625
539_img_.png	0.448	0.582	5.663
436_img_.png	0.525	0.869	4.769
208_img_.png	0.584	0.8001	5.642
322_img_.png	0.4105	0.724	3.767
15_img_.png	0.495	0.767	5.671
619_img_.png	0.483	0.971	5.547
658_img_.png	0.442	0.9801	5.532
910_img_.png	0.405	0.912	5.666
574_img_.png	0.343	0.695	4.064
	0.4705	0.827	5.164

Table 4.2:Results of 10 underwater images from UIEB dataset

Furthermore, to assess the effectiveness of our proposed strategy, conducted a comprehensive evaluation by comparing it with the competitive underwater dehazing method using both qualitative and quantitative analyses, present a selection of sample images that demonstrate the improvements achieved by our strategy in comparison to related approache. Overall, our strategy exhibits notable advantages in terms of perceptual quality enhancement, including improved contrast, reduced color distortion, and enhanced details,when compared to the underwater enhancement method .Additionally, our approach demonstrates greater robustness in handling challenging underwater scenarios.

				Proposed strategy		
	UCIQE	PCQI	UIQM	UCIQE	PCQI	UIQM
199_img_	0.432	0.613	3.412	0.573	0.973	4.625
539_img_	0.401	0.440	4.101	0.448	0.582	5.663
436_img_	0.413	0.515	3.120	0.525	0.869	4.769
208_img_	0.501	0.416	4.130	0.584	0.8001	5.642
322_img_	0.420	0.498	3.101	0.4105	0.724	3.767
910_img_	0.312	0.634	4.111	0.405	0.912	5.666

Table 4.2.1:Comparison of results of 6 underwater images

4.3 Output

Figure 4.1: Color correction of 5 compensated channels.

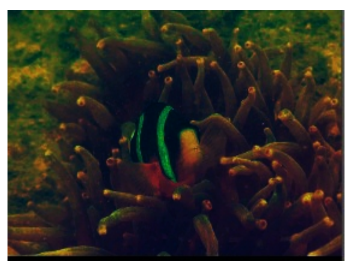

Figure 4.2: Image obtained after performing the white balanced method.

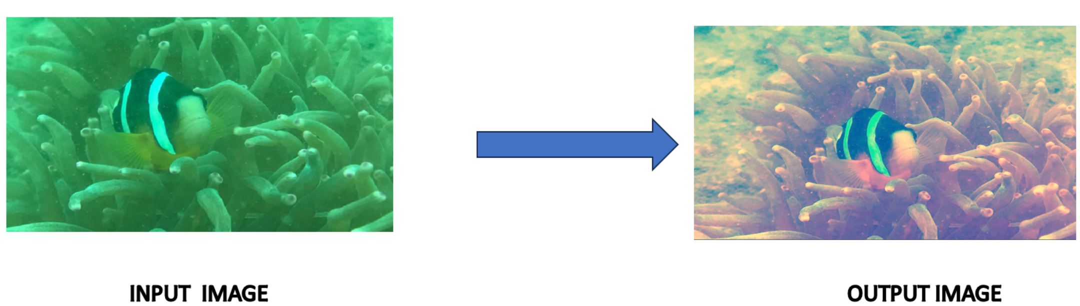

Figure 4.3: Final result of an image.

Chapter 5

Conclusion and Future Works

The method presents a novel approach for enhancing the clarity of underwater single images. The proposed method consists of 3 strategies viz, namely,Transmission map, white-balancing method and multi-scale image fusion .These effectively improves the visual quality of underwater images with varying levels , without the need for specialized equipment or additional information beyond the single input image.One notable advantage of our strategy is its versatility in enhancing images captured in diverse underwater conditions, including natural environments with low light levels and foggy conditions. By enhancing the visual quality and improving the matching capability, our approach contributes to advancements in underwater image analysis and computer vision tasks.The proposed strategy offers a practical solution for enhancing underwater images, making them more visually appealing and suitable for various applications. By utilizing only the available single image, our approach eliminates the need for additional data or complex setups, thus providing a cost-effective and efficient solution for underwater image enhancement.The strategy has obtained good performance for under green coloured underwater images.Additionally, further research should be conducted to improve the method's effectiveness in scenarios with increased depth.

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