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# COLOR BALANCE AND FUSION FOR UNDERWATER IMAGE ENHANCEMENT

**[1]S.H.HITESH KUMAR, [2]Sri P.JAYARAMI REDDY**

[1]M.Tech Student, [2]Assistant Professor,

ECE DEPARTMENT

**Dr. K.V.SUBBA REDDY INSTITUTE OF TECHNOLOGY, Kurnool**

**ABSTRACT:**

Underwater images suffer poor visibility mainly due to scattering and absorption effects. There have been several approaches to restore and enhance the visibility of degraded underwater images. Single image approach without the need of specialized hardware and knowledge about underwater conditions or scene structure is a novel approach for underwater image enhancement. Color compensated and white balanced version of original image as inputs as well as their associated weight maps undergoes a multi-scale fusion strategy. Thus enhanced images are characterized by better exposedness of the dark regions, improved global contrast, and edges sharpness.

## 1. INTRODUCTION

With the fast advance of technologies and the prevalence of imaging devices, billions of digital images are being created every day. Due to undesirable light source, unfavourable weather or failure of the imaging device itself, the contrast and tone of the captured image may not always be satisfactory. In fact, image enhancement algorithms have already been widely applied in imaging devices for tone mapping. For example, in a typical digital camera, the CCD (Charge Coupled Device) or CMOS (Complementary Metal Oxide Semiconductor) array receives the photons passing through lens and then the charge levels are transformed to the original image. Usually, the original image is stored in raw format, with a bit length too big for normal displays.

**PROBLEM DEFINITION:**

An underwater image bears poor quality of images due to the nature of the light. When light enters the water it gets refracted, absorbed and scattered in different directions. Scattering causes the blurring of light and reduces the color contrast. These effects on underwater images are due to the nature of the water. So, image enhancement is the mechanism to process the input image to make it clearly visible as this image enhancement improves the information content and alters the visual impact.

**OBJECTIVE OF PROJECT:**

In this project the image enhancement approach adopts a two step strategy,

- White-balancing
- Image fusion

Combining white-balancing and image fusion, to improve underwater image without restoring. In this approach white-balancing aims at compensating for color cast caused by the selective absorption of colors with depth and image fusion is considered to enhance the edges of the image. Here, we aim for a simple and fast approach that is able to increase the scene visibility in a wide range of underwater images.

**White-Balancing**

Because of the undesirable illuminance or the physical limitations of inexpensive imaging sensors, the captured image may carry obvious color bias. To calibrate the color bias of image, we need to estimate the value of light source, the problem of which called color constancy. Using a suitable physical imaging model, one can get an approximated illuminance, and then a linear transform can be applied to map the original image into an ideal one.

White balance determines color rendition of digital photography's, here it is a typical example for the effect of different white balance settings show in the below Figure 1.3.1. White-balance is an aspect of photography that many digital camera owners don't understand, so for those of you have been avoiding white balancing.

Color cast Daylight white balance

Figure.1.White Balance Image

**Adjustment of White Balancing**

Different digital cameras have different ways of adjusting white balance. Many digital cameras have automatic and semi-automatic modes to help you make the adjustments. White balance basically means color balance. It is a function which gives the camera a reference to "true white". It tells the camera what the color white looks like, so the camera will record it correctly.

**Image Fusion**

Image fusion is a procedure of fusing two or more images of same scene to form single fused image which displays vital information in the fused image. Image fusion technique is used for removing noise from images. The advantages of image fusion includes image sharpening and feature enhancement.

**IMAGE ENHANCEMENT:**

Image Enhancement is one of the most important and difficult techniques in image research. The aim of image enhancement is to improve the visual appearance of an image, or to provide a "better transform representation for future automated image processing. Many images like medical images, satellite images, aerial images and even real life photographs suffer from poor contrast and noise. It is necessary to enhance the contrast and remove the noise to increase image quality. One of the most important stages in medical images detection and analysis is Image Enhancement techniques which improves the quality (clarity) of images for human viewing, removing blurring and noise, increasing contrast, and revealing details are examples of enhancement operations.

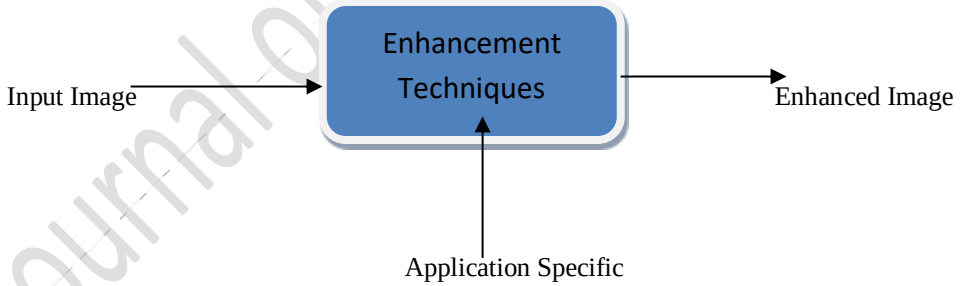


Figure .2.Basic Block Diagram of Image Enhancement

**2. LITERATURE SURVEY**

The fundamental principle of source/receptor relationships is that mass conservation can be assumed and a mass balance analysis can be used to identify and apportion sources of airborne particulate matter in the atmosphere. This methodology has generally been referred to within the air pollution research community as receptor modelling [Hopke, 1985; 1991]. The approach to obtaining a data set for receptor modelling is to determine a large number of chemical constituents such as elemental concentrations in a number of samples. Alternatively, automated electron microscopy can be used to characterize the composition and shape of particles in a series of particle samples.

The authors provide an overview of state-of-the-art image enhancement and restoration techniques for underwater images. Underwater imaging is one of the challenging tasks in the field of image processing and computer vision. Usually, underwater images suffer from non-uniform lighting, low contrast, diminished color, and blurring due to attenuation and scattering of light in the underwater environment. It is necessary to pre-process these images before applying computer vision techniques.

Over the last few decades, many researchers have developed various image enhancement and restoration algorithms for enhancing the quality of images captured in underwater environments. The authors introduce a brief survey on image enhancement and restoration algorithms for underwater images. At the end of the chapter, we present an overview of our approach, which is well accepted by the image processing community to enhance the quality of underwater images. Our technique consists of filtering techniques such as homomorphic filtering, wavelet-based image denoising, bilateral filtering, and contrast equalization, which are applied sequentially. The proposed method increases better image visualization of objects which are captured in underwater environment compared to other existing methods.

## 3. EXISTING AND PROPOSED SYSTEM

Image processing is the manipulation of an image in order to improve its quality, enhances its ability to convey visual information and make it look better. Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image.

The foundations of the DWT go back to 1976 when Croiser, Esteban, and Galand devised a technique to decompose discrete time images. Crochiere, Weber, and Flanagan did a similar work on coding of speech images in the same year. They named their analysis scheme as **subband coding**. In 1983, Burt defined a technique very similar to subband coding and named it **pyramidal coding** which is also known as multiresolution analysis. Later in 1989, Vetterli and Le Gall made some improvements to the subband coding scheme, removing the existing redundancy in the pyramidal coding scheme. Subband coding is explained below. A detailed coverage of the discrete wavelet transform and theory of multiresolution analysis can be found in a number of articles and books that are available on this topic, and it is beyond the scope of this tutorial.

### The Subband Coding and The Multiresolution Analysis:

The main idea is the same as it is in the CWT. A time-scale representation of a digital image is obtained using digital filtering techniques. Recall that the CWT is a correlation between a wavelet at different scales and the image with the scale (or the frequency) being used as a measure of similarity. The continuous wavelet transform was computed by changing the scale of the analysis window, shifting the window in time, multiplying by the image, and integrating over all times. In the discrete case, filters of different cutoff frequencies are used to analyze the image at different scales. The image is passed through a series of high pass filters to analyze the high frequencies, and it is passed through a series of low pass filters to analyze the low frequencies.

This decomposition halves the time resolution since only half the number of samples now characterizes the entire image. However, this operation doubles the frequency resolution, since the frequency band of the image now spans only half the previous frequency band, effectively reducing the uncertainty in the frequency by half. The above procedure, which is also known as the subband coding, can be repeated for further decomposition. At every level, the filtering and subsampling will result in half the number of samples (and hence half the time resolution) and half the frequency band spanned (and hence double the frequency resolution). Figure illustrates this procedure, where x[n] is the original image to be decomposed, and h[n] and g[n] are lowpass and highpass filters, respectively. The bandwidth of the image at every level is marked on the figure as "f".

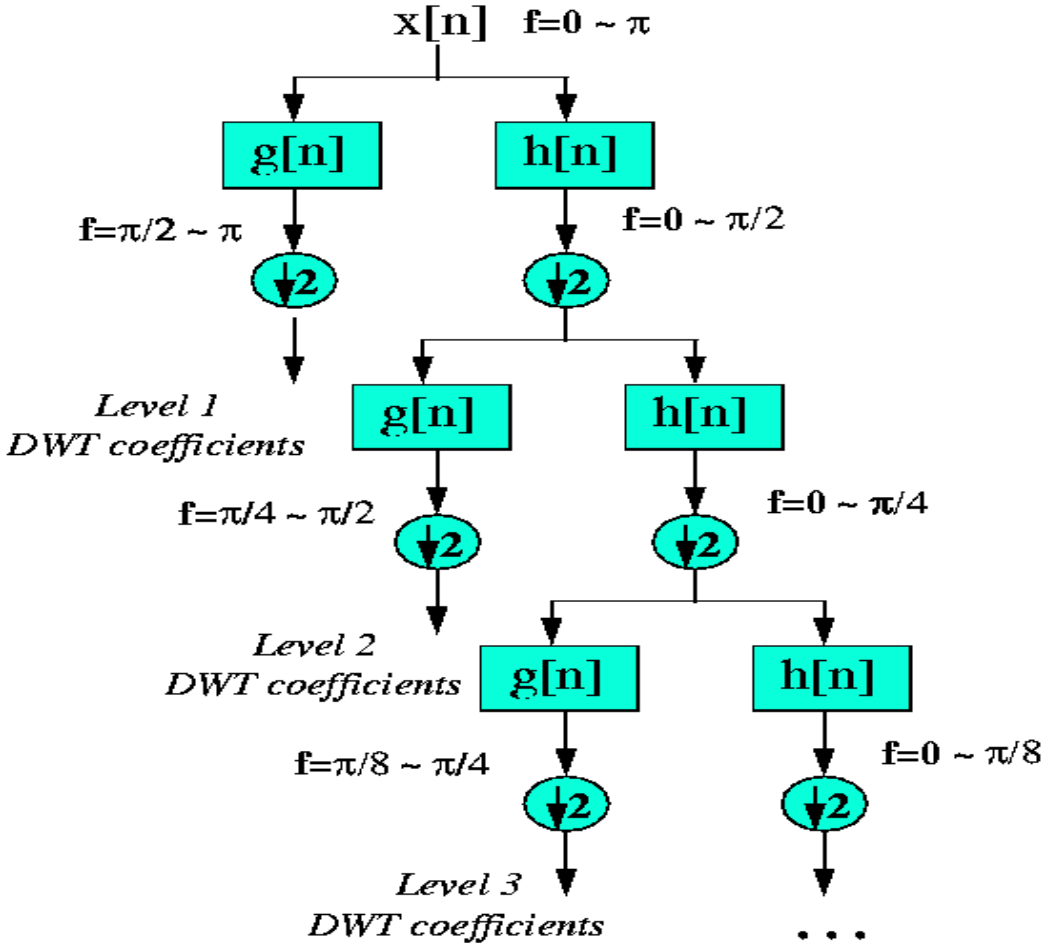


Fig.3. discrete wavelet transform coefficients

The Subband Coding Algorithm

As an example, suppose that the original image x[n] has 512 sample points, spanning a frequency band of zero to □ rad/s. At the first decomposition level, the image is passed through the highpass and lowpass filters, followed by subsampling by 2. The output of the highpass filter has 256 points (hence half the time resolution), but it only spans the frequencies □/2 to □ rad/s (hence double the frequency resolution). These 256 samples constitute the first level of DWT coefficients. The output of the lowpass filter also has 256 samples, but it spans the other half of the frequency band, frequencies from 0 to □/2 rad/s. This image is then passed through the same lowpass and highpass filters for further decomposition.

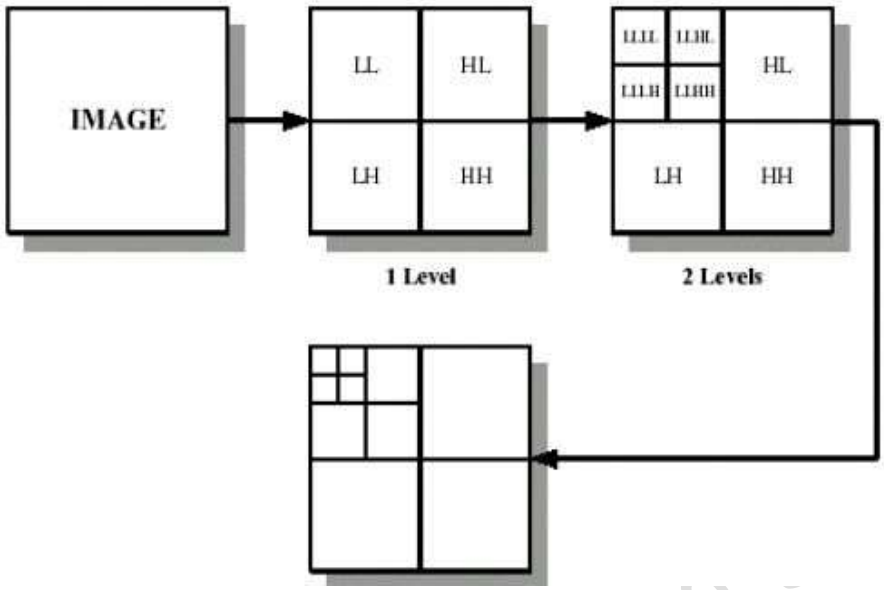


Figure:4. 2D IMAGE dwt operation

The output of the second lowpass filter followed by subsampling has 128 samples spanning a frequency band of 0 to □/4 rad/s, and the output of the second highpass filter followed by subsampling has 128 samples spanning a frequency band of □/4 to □/2 rad/s. The second highpass filtered image constitutes the second level of DWT coefficients. This image has half the time resolution, but twice the frequency resolution of the first level image. In other words, time resolution has decreased by a factor of 4, and frequency resolution has increased by a factor of 4 compared to the original image. The lowpass filter output is then filtered once again for further decomposition. This process continues until two samples are left. For this specific example there would be 8 levels of decomposition, each having half the number of samples of the previous level. The DWT of the original image is then obtained by concatenating all coefficients starting from the last level of decomposition (remaining two samples, in this case). The DWT will then have the same number of coefficients as the original image.

The frequencies that are most prominent in the original image will appear as high amplitudes in that region of the DWT image that includes those particular frequencies. The difference of this transform from the Fourier transform is that the time localization of these frequencies will not be lost. However, the time localization will have a resolution that depends on which level they appear. If the main information of the image lies in the high frequencies, as happens most often, the time localization of these frequencies will be more precise, since they are characterized by more number of samples. If the main information lies only at very low frequencies, the time localization will not be very precise, since few samples are used to express image at these frequencies. This procedure in effect offers a good time resolution at high frequencies, and good frequency resolution at low frequencies. Most practical images encountered are of this type.

**4. PROPOSED SYSTEM:**

Underwater environment offers many rare attractions such as marine animals and fishes, Different from common images, underwater images suffer from poor visibility resulting from the attenuation of the propagated light, mainly due to absorption and scattering effects. The absorption substantially reduces the light energy, while the scattering causes changes in the light propagation direction. They result in foggy appearance and contrast degradation making distant objects misty. Practically, in common sea water images, the objects at a distance of more than 10 meters are almost unperceivable, and the colors are faded because their composing wavelengths are cut according to the water depth.

There have been several attempts to restore and enhance the visibility of such degraded images. Since the deterioration of underwater scenes results from the combination of multiplicative and additive processes traditional enhancing techniques such as gamma correction, histogram equalization appear to be strongly limited for such a task. Works that are the problem has been tackled by tailored acquisition strategies using multiple images, specialized hardware or polarization filters. In contrast, this paper introduces a novel approach to remove the haze in underwater images based on a single image captured with a conventional camera.

Our approach builds on the fusion of multiple inputs, but derives the two inputs to combine by correcting the contrast and by sharpening a white-balanced version of a single native input image. Our approach builds on the fusion of multiple inputs, but derives the tw0inputs to combine by correcting the contrast and by sharpening a white-balanced version of a single native input image.

**Light Propagation in Underwater:**

For an ideal transmission medium they received light is influenced mainly by the properties of the target objects and the camera lens characteristics. This is not the case underwater. First, the amount of light available under water, depends on several factors. The interaction between the sun light and the sea surface is affected by the time of the day (which influences the light incidence angle), and by the shape of the interface between air and water (rough vs. calm sea). The diving location also directly impacts the available light, due to a location-specific color cast: deeper seas and oceans induce green and blue casts; tropical waters appear cyan, while protected reefs are characterized by high visibility. In addition to the variable amount of light available under water, the density of particles that the light has to go through is several hundreds of times denser in seawater than in normal atmosphere.

As a consequence, sub-sea water absorbs gradually different wavelengths of light. Red, which corresponds to the longest wavelength, is the first to be absorbed (10-15 ft), followed by orange (20-25 ft), and yellow (35-45 ft). Pictures taken at 5 ft depth will have a noticeable loss of red. Further-more, the refractive index of water makes judging distances difficult. As a result, underwater objects can appear 25% larger than they really are.

The comprehensive studies have shown that the total irradiance incident on a generic point of the image plane has three main components in underwater mediums: direct component, forward scattering and back scattering.

The direct component is the component of light reflected directly by the target object onto the image plane. At each image coordinate $x$ the direct component is expressed as

$$E_D(x) = J(x)e^{-\eta d(x)} = J(x)t(x)$$

Where J $(x)$ is the radiance of the object, $d(x)$ is the distance between the observer and the object, and $\eta$ is the attenuation coefficient. The exponential term $e^{-\eta d(x)}$ is also known as the transmission $t(x)$ through the underwater medium.

Besides the absorption, the floating particles existing in the underwater mediums also cause the deviation (scattering) of the incident rays of light. Forward-scattering results from a random deviation of a light ray on its way to the camera lens. Back-scattering is due to the artificial light (e.g. flash) that hits the water particles, and is reflected back to the camera. Back-scattering acts like a glaring veil superimposed on the object. Mathematically, it is often expressed as shown below in Eq.2 and Eq.3.

$$I(x) = J(x)e^{-\eta d(x)} + B_S(x)(1 - e^{-\eta d(x)})$$

$$E_{BS}(x) = B_S(x)(1 - e^{-\eta d(x)})$$

**Underwater White Balance:**

In our approach, white balancing aims at compensating for the color cast caused by the selective absorption of colors with depth, while image fusion is considered to enhance the edges and details of the scene, to mitigate the loss of contrast resulting from back-scattering. We now focus on the white-balancing stage.

White-balancing aims at improving the image aspect, primarily by removing the undesired color castings due to various illumination or medium attenuation properties. In underwater, the perception of color is highly correlated with the depth, and an important problem is the green-bluish appearance that needs to be rectified. Since the scattering attenuates more the long wavelengths than the short ones, the color perception is affected as we go down in deeper water.

In practice, the attenuation and the loss of color also depends on the total distance between the observer and the scene. To compensate for the loss of red channel, we build on the four following observations/principles: The green channel is relatively well preserved under water, compared to the red and blue ones. Light with a long wavelength, i.e. the red light, is indeed lost first when travelling in clear water. The green channel is the one that contains opponent color information compared to the red channel, and it is thus especially important to

compensate for the stronger attenuation induced on red, compared to green. Therefore, we compensate the red attenuation by adding a fraction of the green channel to red. We had initially tried to add both a fraction of green and blue to the red but, using only the information of the green channel allows to better recover the entire color spectrum while maintaining a natural appearance of the background (water regions).

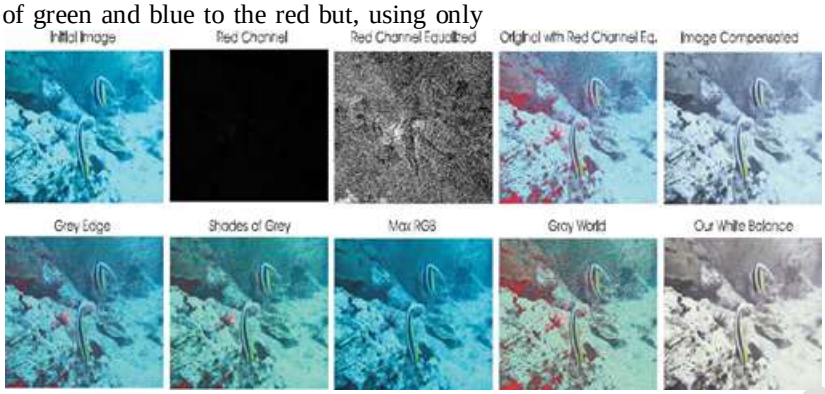


Figure : 5. Underwater White-Balancing

- The compensation should be proportional to the difference between the mean green and the mean red values because, under the Gray world assumption (all channels have the same mean value before attenuation), this difference reflects the disparity/unbalance between red and green attenuation.
- To avoid saturation of the red channel during the Gray World step that follows the red loss compensation, the enhancement of red should primarily affect the pixels with small red channel values, and should not change pixels that already include a significant red component.
- In other words, the green channel information should not be transferred in regions where the information of the red channel is still significant. Basically, the compensation of the red channel has to be performed only in those regions that are highly attenuated telling that if a pixel has a significant value for the three channels, this is because it lies in a location near the observer, or in an artificially illuminated area, and does not need to be restored.Mathematically, to account for the above observations, we propose to express the compensated red channel $I_{r\ c}$ at every pixel location $(x)$ as follows

$$Irc\ (x) = Ir(x) + \alpha.(Ig-\overline{Ir}).(1-\overline{Ir}(x)).Ig(x)$$

Where $I_r$ , $I_g$ represent the red and green color channels of image I, each channel being in the interval [0, 1], after normalization by the upper limit of their dynamic range; while $I_r$ and $I_g$ denote the mean value of $I_r$ and $I_g$ .each factor in the second term directly results from one of the above observations, and $\alpha$ denotes a constant parameter. In practice, our tests have revealed that a value of $\alpha = 1$ is appropriate for various illumination conditions and acquisition settings. To complete our discussion about the severe and color-dependent attenuation of light under water, it is worth noting the works in, which reveal and exploit the fact that, in turbid waters or in places with high concentration of plankton, the blue channel may be significantly attenuated due to absorption by organic matter. To address those cases, when blue is strongly attenuated and the compensation of the red channel appears to be insufficient, we propose to also compensate for the blue channel attenuation, i.e. we compute

$$Ibc(x) = Ib(x) + \alpha.(Ig - Ib).(1-Ib(x)).Ig(x)$$

Our white-balancing approach reduces the quantization artifacts introduced by domain stretching (the red regions in the different outputs). The reddish appearance of high intensity regions is also well corrected since the red channel is better balanced, our approach shows the highest robustness compared to the other well-known white-balancing techniques. In particular, whilst being conceptually simplest, in cases for which the red channel of the underwater image is highly attenuated, it outperforms the white balancing strategy introduced in our conference version of our fusion-based underwater dehazing method.

**Multi-Scale Fusion**

- **Inputs of Multi Fusion**

Since the color correction is critical in underwater, we first apply our white balancing technique to the original image. This step aims at enhancing the image appearance by discarding unwanted color casts caused by various illuminants. In water deeper than 30 ft, white balancing suffers

from noticeable effects since the absorbed colors are difficult to be recovered. As a result, to obtain our ***first input*** we perform a gamma correction of the white balanced image version. Gamma correction aims at correcting the global contrast and is relevant since; in general, white balanced underwater images tend to appear too bright.

To compensate for this loss, we derive a ***second input*** that corresponds to a sharpened version of the white balanced image. Therefore, we follow the unsharp masking principle, in the sense that we blend a blurred or unsharp (here Gaussian filtered) version of the image with the image to sharpen.

The typical formula for unsharp masking defines the sharpened image $S$ as $S = I + \beta (I - G * I)$, where $I$ is the image to sharpen (in our case the white balanced image), $G * I$ denotes the Gaussian filtered version of $I$, and $\beta$ is a parameter. In practice, the selection of $\beta$ is not trivial. A small $\beta$ fails to sharpen $I$, but a too large $\beta$ results in over-saturated regions, with brighter highlights and darker shadows. To circumvent this problem, we define the sharpened image $S$ as follows:

$$S = (I + N\{I - G * I\})/2, \qquad \textbf{...(Eq.6)}$$

With $N\{.\}$ denoting the linear normalization operator, also named histogram stretching in the literature. This operator shifts and scales all the color pixel intensities of an image with a unique shifting and scaling factor defined so that the set of transformed pixel values cover the entire available dynamic range.

The sharpening method defined is referred to as normalized unsharp masking process in the following. It has the advantage to not require any parameter tuning, and appears to be effective in terms of sharpening. This second input primarily helps in reducing the degradation caused by scattering. Since the difference between white balanced image and its Gaussian filtered version is a high pass signal that approximates the opposite of Laplacian, this operation has the inconvenient to magnify the high-frequency noise, thereby generating undesired artifacts in the second input.

- **Weights of the Fusion Process:** The weight maps are used during blending in such a way that pixels with a high weight value are more represented in the final image. They are thus defined based on a number of local image quality or saliency metrics.
- **Laplacian contrast weight** ($W_L$)**:** estimates the global contrast by computing the absolute value of a Laplacian filter applied on each input luminance channel. This straightforward indicator was used in different applications such as tone mapping and extending depth of field since it assigns high values to edges and texture. For the underwater dehazing task, however, this weight is not sufficient to recover the contrast, mainly because it cannot distinguish much between a ramp and flat regions. To handle this problem, we introduce an additional and complementary contrast assessment metric.
- **Saliency weight** ($W_S$**)** aims at emphasizing the salient objects that lose their prominence in the underwater scene. This computationally efficient algorithm has been inspired by the biological concept of center surround contrast. However, the saliency map tends to favour highlighted areas (regions with high luminance values). To overcome this limitation, we introduce an additional weight map based on the observation that saturation decreases in the highlighted regions.
- **Saturation weight** ($W_{S\,at}$**)** enables the fusion algorithm to adapt to chromatic information by advantaging highly saturated regions. This weight map is simply computed (for each input $I_k$) as the deviation (for every pixel location) between the $R_k$ ,$G_k$ and $B_k$ color channels and the luminance $L_k$ of the $k^{th}$ input. We explain this observation as follows. The exposedness weight map had been introduced to reduce the weight of pixels that are under- or over-exposed. Hence, this weight map assigns large (small) weight to input pixels that are close to the middle of the image dynamic range. In our case, since the gamma corrected input tends to exploit the whole dynamic range, the use of the exposedness weight map tends to penalize it in favour of the sharpened image, thereby inducing some sharpening artifacts and missing some contrast enhancements.
- **Naive Fusion Process** Given the normalized weight maps, the reconstructed image $R(x)$ could typically be obtained by fusing the defined inputs with the weight measures at every pixel location $(x)$ Where $I_k$ denotes the input ($k$ is the index of the inputs - $K = 2$ in our case) that is weighted by the normalized weight maps $W_k$ . In practice, the naive approach introduces undesirable halos. A common solution to overcome this limitation is to employ multi-scale linear or non-linear filters.
- **Multi-Scale Fusion Process** The pyramid representation decomposes an image into a

sum of band pass images. In practice, each level of the pyramid does filter the input image using a low-pass Gaussian kernel $G$, and decimates the filtered image by a factor of 2 in both directions. It then subtracts from the input an up-sampled version of the low-pass image, thereby approximating the (inverse of the) Laplacian, and uses the decimated low-pass image as the input for the subsequent level of the pyramid. In this equation, $L_l$ and $G_l$ represent the $l^{th}$ level of the Laplacian and Gaussian pyramid, respectively. To write the equation, all those images have been up-sampled to the original image dimension. However, in an efficient implementation, each level $l$ of the pyramid is manipulated at native sub sampled resolution. Following the traditional multi-scale fusion strategy, each source input $I_k$ is decomposed into a Laplacian pyramid while the normalized weight maps $W_k$ are decomposed using a Gaussian pyramid. Both pyramids have the same number of levels, and the mixing of the Laplacian inputs with the Gaussian normalized weights is performed independently at each level.

## 5. DESIGN AND IMPLEMENTATION

### 5.1. INTRODUCTION:

In this project our white-balancing aim at compensating for the color cast caused by selective absorption of color with depth. Primarily by removing the undesired color casting due to various illumination or medium attenuation properties. Image fusion is to improve underwater images without restoring. Here the results are executed in MATLAB software .Image processing toolbox is used to perform analysis and algorithm development which perform image segmentation, image enhancement and noise reduction.

### 5.2. SYSTEM ARCHITECTURE:

In this project a single image is given as input image and our white-balancing approach derived into two images one is the input 1 and input 2 as shown in the Figure using gamma correction and edge sharpening and the two input images are used as inputs of the fusion process. Multi-scale fusion approach is here to examine with three levels by weight maps calculation.

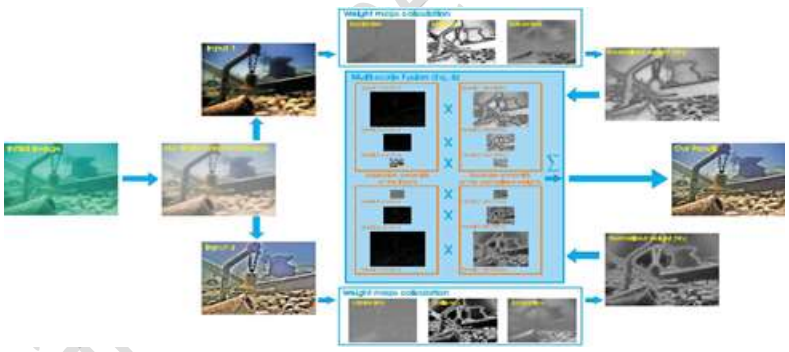

Figure 5 System Architecture Diagram

The weight maps tends to amplify some artifacts such as ramp edges of our second input and to reduce the benefits derived from the gamma corrected image in terms of image contrast. This second input corresponds to a sharpened version of the white balanced image. Second input primarily helps in reducing the degradation caused by scattering. The weight maps are used during blending in such a way that pixels with high weight value are more represented in the final image.

## 6. RESULTS

### 6.1. OUTPUT SCREENS:

- Select the input image as shown in the Figure 6.1. (a) and click on open.

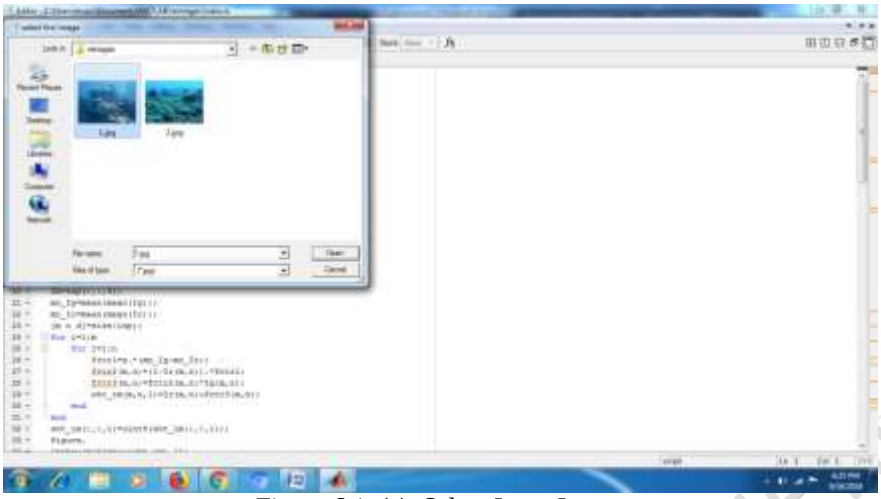

Figure 6.1. (a). Select Input Image

Figure 6.1. (b). Input Image

- Run the main file by clicking on run button. The input image is displayed first. As shown in the Figure above is the given input image from this single input image two images are derived from the white-balancing. White-balancing aims at compensating for color cast caused by the selective absorption of colors with depth.

**Red channel image:**

Figure 6.1. (c). Red Channel Image

- As shown in the above Figure 6.1. (c) is the Red channel image. Underwater images are highly correlated with the depth and typically exhibits color distortion and low contrast. Depending on wavelengths and attenuation rates red color is the one that attenuates the fastest. So, from the input image the red channel image is recovered.

**Blue channel image:**

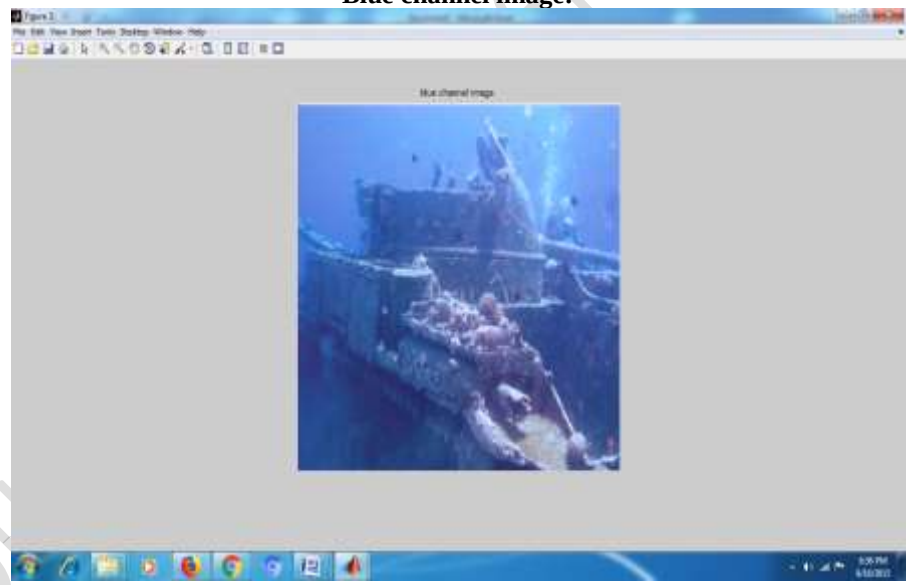

Figure 6.1. (d). Blue Channel Image.

- As shown in the Figure 6.1. (d) Blue channel image is compensated. In fact that turbid waters blue channel may be significantly attenuated due to the absorption by organic matter then the red channel may appears to be insufficient if the blue is strongly attenuated.

**Sharpened image:**

Figure 6.1. (e).Sharpened Image

- As shown in the Figure 6.1. (e) the edges are sharpened in this image.

**Fused image:**

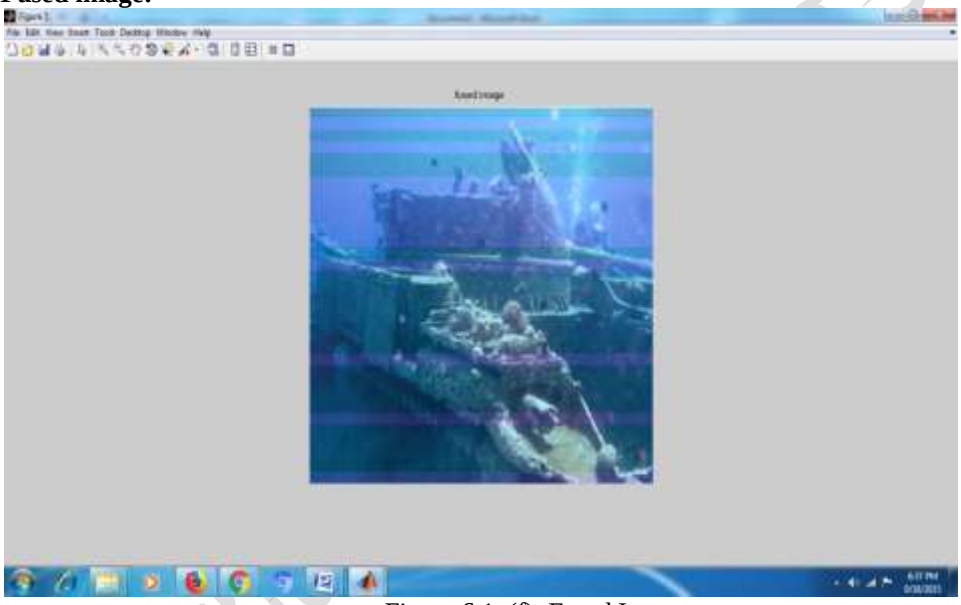

Figure 6.1. (f). Fused Image

As shown in the Figure 6.1. (f) fused image builds on the set of inputs and weight maps derived from single image. This fused image is defined based on number of local image quality. In this Figure we can see the difference between the input image and fused image as the fused image is clear with color and quality of the image. Finally we calculate and get the values of MSE and psnr to know the quality of the image.

## 7. CONCLUSION

### 7.1. FINAL CONCLUSION:

In this paper, we have presented an alternative approach to enhance underwater images. Our strategy builds on the fusion principle and does not require additional information than the single original image. We have shown in our experiments that our approach is able to enhance a wide range of underwater images (e.g. different cameras, depths, light conditions) with high accuracy, being able to recover important faded features and edges. Moreover, for the first time, we demonstrate the utility and relevance of the proposed image enhancement technique for several challenging underwater computer vision applications.

### 7.2. FUTURE SCOPE:

Our future scope is focussed on patch segmentation fusion. An image is first split into small

patches and the segmentation is performed on each patch. Here, sharpening method is used to smooth the edges to increase the visibility of the underwater image in wide range. Our future scope is focussed on patch segmentation.

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