Chapter 2

An Image Based Technique for Enhancement of Underwater Images

In this chapter, we proposed an efficient approach for enhancing the quality of degraded underwater images. Applying computer vision techniques directly on the captured underwater images doesn’t yield good results. In order to enhance the quality of underwater image, we proposed technique which consists of combination of different individual filters applied sequentially on the degraded underwater images. The performance of the proposed approach is compared with state-of-the-art approach and the experimental result shows that our approach yields better results.

2.1 Introduction

Optical imaging in underwater environment offers scientist high levels of detail and ease of interpretation. Physical properties of the underwater medium cause degradation effects not present in normal images taken in air. Figure 2.1 shows the degraded underwater images which are suffered from blur, non-uniform illumination, haze and sunlight flicker. The light in underwater environment suffers from significant attenuation and backscatter, limiting the practical coverage of a single image to only a few square meters. The visible spectrum in water has attenuation lengths of the order of meters, thus most underwater vehicles carry out optical imaging surveys using their own light source. Underwater images are essentially characterized by their poor visibility because light is exponentially attenuated as it travels in the water and the scenes result poorly contrasted and hazy. 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 absorption (which removes light energy) and scattering (which changes the direction of light path) [117]. The Figure 2.2 shows the absorption and scattering phenomenon in underwater environment. The absorption and
scattering processes of the light in water influence the overall performance of underwater imaging systems. Forward scattering (randomly deviated light on its way from an object to the camera) generally leads to blurring of the image features. On the other hand, backward scattering (the fraction of the light reflected by the water towards the camera before it actually reaches the objects in the scene) generally limits the contrast of the images, generating a characteristic veil that superimposes itself on the image and hides the scene.

Absorption and scattering effects are not only due to the water itself but also to other components such as dissolved organic matter or small observable floating particles. The presence of the floating particles known as marine snow (highly variable in kind and concentration) increase absorption and scattering effects. The visibility range can be increased with artificial lighting (Autonomous Underwater Vehicles uses strobe light as artificial lighting) but it creates casting shadows that moves across the scene as the vehicle moves. Further, power and/or size limitations lead to lighting patterns that are far from uniform. This producing a bright spot in the center of the image with a poorly illuminated area surrounding it. Finally, as the amount of light is reduced when we go deeper, colors drop off one by one depending on their wavelengths. The images we are interested suffer from following problems: limited range visibility, low contrast, non uniform lighting, blurring, bright artifacts, color diminished and noise.

Over the last few decades, a large number of researchers have contributed their work for enhancing the quality of underwater images for various general-purpose applications. The research on underwater image processing can be addressed from two different points of view such as an image restoration or an image enhancement method [117]. (i) Image restoration aims to recover a degraded image using a model of the degradation and of the original image formation; it is essentially an inverse problem. These methods are rigorous, but they require many model parameters like attenuation and diffusion coefficients that characterize the water turbidity and can be extremely variable. Another important parameter required is the depth estimation of a given object in the scene. Whereas, (ii) Image enhancement technique uses qualitative subjective criteria to produce a more visually pleasing image and these methods do not rely on any physical model for the image formation. These kinds of approaches are usually simpler and faster than deconvolution methods. Therefore, in
this chapter we present an image enhancement approach by using combination of different individual filters which are cascaded together.

2.1.1 Related Work on Underwater Image Restoration

Image restoration aims at recovering the original image $f(x,y)$ from the observed image $g(x,y)$ using explicit knowledge about the degradation function $h(x,y)$ (also called point spread function PSF) and the noise characteristics $n(x,y)$:

$$ g(x,y) = f(x,y) * h(x,y) + n(x,y), $$

(2.1)
Figure 2.2: Components of light propagating in a underwater environment: direct component (−), light ray which is reflected by an objects surface (· · ·) and the backscattered component (− · · ·), the light scattered by the medium. (courtesy Erickson Nascimento et al.)

where \( \ast \) denotes convolution. The degradation function \( h(x, y) \) includes the system response from the imaging system itself and the effects of the medium (water). In the frequency domain, it is given by:

\[
G(u, v) = F(u, v)H(u, v) + N(u, v),
\]

(2.2)

where \((u, v)\) are spatial frequencies and \(G, F, H\) and \(N\) are Fourier transforms of \(g, f, h\) and \(n\) respectively. The system response function \(H\) in the frequency domain is referred as the optical transfer function (OTF) and its magnitude is referred as modulation transfer function (MTF). Usually, the system response is expressed as a direct product of the optical system itself and the medium:

\[
H(u, v) = H_{Optical System}(u, v)H_{medium}(u, v).
\]

(2.3)
The better the knowledge about the degradation function, the better are the results of the restoration. However, in practical cases, there is insufficient knowledge about the degradation and it must be estimated and modeled. The main source of degradation in underwater imaging includes turbidity, floating particles and the optical properties of light propagation in water. Therefore, underwater optical properties have to be incorporated into the PSF and MTF. The presence of noise from various sources further complicates these techniques.

Hou et al., [58, 59, 60] incorporated the underwater optical properties to the traditional image restoration approach. They assume that blurring is caused by strong scattering due to water and its constituents which include various sized particles. To address this issue, they incorporated measured in-water optical properties to the point spread function in the spatial domain and the modulation transfer function in frequency domain. The authors modeled $H_{\text{medium}}$ for circular symmetric response systems (2-dimensional space) as an exponential function

$$H_{\text{medium}}(\phi, r) = \exp\{-D(\phi)r\}.$$  \hfill (2.4)

The exponent, $D(\phi)$, is the decay transfer function obtained by Wells [138] for the seawater within the small angle approximation

$$D(\phi) = c - \frac{b(1 - \exp\{-2\pi\theta_0\phi\})}{2\pi\theta_0\phi},$$  \hfill (2.5)

where $\theta_0$ is the mean square angle, $b$ and $c$ are the total scattering and attenuation coefficients, respectively.

Trucco and Olmos [135] presented a self-tuning restoration filter based on a simplified version of the Jaffe-McGlamery [65] image formation model. Two assumptions are made in order to design the restoration filter. The first one assumes uniform illumination (direct sunlight in shallow waters) and the second one is to consider only the forward component $E_f$ of the image model as the major degradation source, ignoring back scattering $E_b$ and the direct component $E_d$. This appears reasonable whenever the concentration of particulate matter generating backscatter in the water column is limited.

Liu et al., [82] measured the PSF and MTF of seawater in the laboratory by means of the image transmission theory and used Wiener filters to restore the blurred underwater
images. The degradation function $H(u, v)$ is measured in a water tank. An experiment is constructed with a slit image and a light source. In a first step, one dimensional light intensity distribution of the slit images at different water path lengths is obtained. The one dimensional PSF of sea water can be obtained by the deconvolution operation. Then, according to the property of the circle symmetry of the PSF of seawater, the 2-dimensional PSF can be calculated by mathematical method. In a similar way, MTFs are derived. These measured functions are used for blurred image restoration. The standard wiener deconvolution process in applied. The transfer function $W(u, v)$ reads

$$W(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + S_n/S_f},$$

(2.6)

where $S_n$ and $S_f$ are the power spectrum of noise and original image respectively, and $H^*(u, v)$ is the conjugate matrix of $H(u, v)$. Noise is regarded as white gaussian noise, and $S_n$ is a constant that can be estimated from the blurred images with noise while $S_f$ is estimated as

$$S_f = \frac{S_g(u, v) - S - n(u, v)}{|H(u, v)|^2},$$

(2.7)

where $S_g$ is the power spectrum of the blurred image. Then, the spectrum of the restored image is

$$F(u, v) = G(u, v) \frac{H^*(u, v)}{|H(u, v)|^2 + S_n/S_f}.$$  

(2.8)

2.1.2 Related Work on Underwater Image Enhancement

Image enhancement methods make total abstraction of the image formation process, and no a priori knowledge of the environment is needed (i.e. these methods do not use attenuation and scattering coefficients). They are usually simpler and faster than the image restoration techniques. Bazeille et al., [9] proposed an algorithm to preprocess underwater images. It reduces underwater perturbations and improves image quality. It is composed of several successive independent processing steps which correct non-uniform illumination (homomorphic filtering), suppress noise (wavelet denoising), enhance edges (anisotropic filtering) and adjust colors (equalizing RGB channels to suppress predominant color). The algorithm is automatic and requires no parameter adjustment.
Arnold-Bos et al., [4] presented a complete preprocessing framework for underwater images. They investigated the possibility of addressing the whole range of noises present in underwater images by using a combination of deconvolution and enhancement methods. First, a contrast equalization system is proposed to reject backscattering, attenuation and lighting inequalities. If $I(i, j)$ is the original image and $I_{LP}(i, j)$ its low-pass version, a contrast-equalized version of $I$ is $I_{eq} = I / I_{LP}$. The additional use of adaptive smoothing helps to address the remaining sources of noise, which is corresponding to sensor noise, floating particles and miscellaneous quantification errors. This method applies local contrast equalization method as a first step in order to deal with non-uniform lighting caused by backscattering. Generally, contrast equalization will raise the noise level in poorly contrasted areas of the original image. Signal to noise ratio would remain constant after equalization; but the fixed color quantization step induces strong errors in dark zones. Compared to the local contrast equalization method, the homomorphic filtering (which adopts the illumination-reflectance model) has a slightly more important effect on noise in dark zones. Remaining noises corresponding to sensor noise, floating particles and miscellaneous quantification errors are suppressed using a generic self-tuning wavelet-based algorithm.

Chambah et al., [21] proposed a color correction method based on Automatic Color Equalization (ACE) model, an unsupervised color equalization algorithm developed by Rizzi et al., [113]. ACE is a perceptual approach inspired by some adaptation mechanisms of the human vision system, in particular lightness constancy and color constancy. ACE was applied on videos taken in aquatic environment that present a strong and non-uniform color cast due to the depth of the water and the artificial illumination. Images were taken from the tanks of an aquarium. Inner parameters of the ACE algorithm were properly tuned to meet the requirements of image and histogram shape naturalness and to deal with these kinds of aquatic images. Iqbal et al., [61] presented an underwater image enhancement method using an integrated color model. They proposed an approach based on slide stretching: first, contrast stretching of RGB algorithm is used to equalize the color contrast in the images. Second, saturation and intensity stretching of HSI is applied to increase the true color and solve the problem of lighting. The blue color component in the image is controlled by the saturation and intensity to create the range from pale blue to deep blue. The contrast ratio is therefore controlled by decreasing or increasing its value.
Rafael Garcia et al., [44] proposed an approach to solve lighting problems in underwater imaging. The approach proposed is slightly modified to adapt them to the peculiarities of the underwater environment. The author carried out a sequence of steps to solve lighting problems, illumination-reflectance model, local histogram equalization, homomorphic filtering and subtraction of the illumination field by polynomial adjustment.

In this chapter, we presented an approach for enhancing the quality of underwater images, which is well accepted by image processing community. Since, the underwater image restoration method requires many model parameters to employ deconvolution technique on degraded underwater images and it is very difficult to estimate the physical model parameters of underwater. Therefore, we employed image enhancement method, which doesn’t require these parameters. Our approach consists of filters such as homomorphic filtering, wavelet denoising, bilateral filtering and contrast stretching which are applied sequentially. Initially, we apply homomorphic filter to correct non-uniform illumination of light. Homomorphic filter simultaneously normalizes the brightness across an image and increases contrast. The homomorphic filtering performs in the frequency domain and it adopts the illumination and reflectance model. After correcting non-uniform illumination, wavelet based denoising using modified BayesShrink is employed to remove random additive Gaussian noise which is usually present in underwater images. The main objective of these types of random noise removal is to suppress the noise while preserving the original image details. Further, we employed bilateral filter to smooth the image while preserving edges and enhance them. Finally, we apply contrast stretching which stretches the range of intensity values and evenly distributes color values across the image.

The remaining sections of the chapter is organized as follows: section 2.2 describes proposed technique in detail. The experimental results are presented in the section 2.3. Finally, the section 2.4 concludes the chapter.

2.2 Our Approach

In this section, we present different individual filters, which are employed sequentially on degraded underwater images to enhance image visual quality.
2.2.1 Homomorphic Filtering

The homomorphic filtering is used to correct non-uniform illumination and to enhance contrasts in the image. It’s a frequency filtering, preferred to others techniques because it corrects non-uniform lighting and sharpens the image features at the same time.

We consider that image is a function of the product of the illumination and the reflectance as shown below:

\[ f(x,y) = i(x,y) \cdot r(x,y), \]  

where \( f(x,y) \) is the image sensed by the camera, \( i(x,y) \) the illumination multiplicative factor, and \( r(x,y) \) the reflectance function. If we take into account this model, we assume that the illumination factor changes slowly through the view field; therefore it represents low frequencies in the Fourier transform of the image. On the contrary reflectance is associated with high frequency components. By multiplying these components by a high-pass filter we can then suppress the low frequencies i.e., the non-uniform illumination in the image. The algorithm can be decomposed as follows:

- Separation of the illumination and reflectance components by taking the logarithm of the image. The logarithm converts the multiplicative into an additive one.

\[ g(x,y) = ln(f(x,y)) = ln(i(x,y) \cdot r(x,y)) = ln(i(x,y)) + ln(r(x,y)). \]  

- Computation of the Fourier transform of the log-image

\[ G(w_x, w_y) = I(w_x, w_y) + R(w_x, w_y). \]  

- High-pass filtering. The filter applied to the Fourier transform decreases the contribution of low frequencies (illumination) and also amplifies the contribution of mid and high frequencies (reflectance), sharpening the image features of the objects in the image

\[ S(w_x, w_y) = H(w_x, w_y) \cdot I(w_x, w_y) + H(w_x, w_y) \cdot R(w_x, w_y), \]
with,
\[ H(w_x, w_y) = (r_H - r_L)(1 - \exp\left(-\frac{w_x^2 + w_y^2}{2\delta_w^2}\right)) + r_L. \] (2.13)

where \( r_H = 2.5 \) and \( r_L = 0.5 \) are the maximum and minimum coefficients values and \( \delta_w \) a factor which controls the cutoff frequency. These parameters are selected empirically.

- Computation of the inverse Fourier transform to come back in the spatial domain and then taking the exponent to obtain the filtered image.

### 2.2.2 Wavelet Thresholding and Threshold Selection

Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with the essential signal characteristics and with the less noise.

A simple denoising algorithm that uses the wavelet transform consist of the following three steps, (1) Calculate the wavelet transform of the noisy signal (2) Modify the noisy detail wavelet coefficients according to some rule (3) Compute the inverse transform using the modified coefficients.

Let us consider a signal \( \{f_{ij}, i, j = 1, ..., N\} \), where \( N \) is some integer power of 2. It has been corrupted by additive noise and one observes
\[ g_{ij} = f_{ij} + \varepsilon_{ij}, \quad i, j = 1, ..., N, \] (2.14)

where \( \varepsilon_{ij} \) are independent and identically distributed (i.i.d.) zero mean, white Gaussian noise with standard deviation \( \sigma \) i.e. \( \mathcal{N}(0, \sigma^2) \) and independent of \( f_{ij} \). From this noisy signal \( g_{ij} \), we want to find an approximation \( \hat{f}_{ij} \). The goal is to remove the noise, or denoise \( g(i, j) \),
Figure 2.3: Subbands of the 2-D orthogonal wavelet transform.

and to obtain an estimate \( \hat{f}_{ij} \) and \( f_{ij} \) which minimizes the mean squared error (MSE),

\[
MSE(\hat{f}) = \frac{1}{N^2} \sum_{i,j=1}^{N} (\hat{f}_{ij} - f_{ij})^2. \tag{2.15}
\]

Let \( g = \{g_{ij}\}_{ij} \), \( f = \{f_{ij}\}_{ij} \), and \( \varepsilon = \{\varepsilon_{ij}\}_{ij} \); denote the matrix representation of the image under consideration. Let \( D = \mathcal{W} g \), \( C = \mathcal{W} f \), \( \varepsilon = \mathcal{W} e \); denote the matrix of wavelet coefficients \( g, f, e \) respectively. Where, \( \mathcal{W} \) is the two-dimensional dyadic orthogonal wavelet transform operator. It is convenient to label the subbands of the transform as shown in Figure 2.3. The subbands, \( HH_k, HL_k, LH_k \) are called the details, where \( k = 1, \ldots, J \) is the scale, with \( J \) being the largest (or coarsest) scale in the decomposition and a subband at scale \( k \) has size \( N/2^k \times N/2^k \). The subband \( LL_j \) is the low resolution residual and is typically chosen large enough such that \( N/2^j \geq N, N/2^j \geq 1 \). The wavelet-thresholding denoising method filters each coefficient \( G_{ij} \) from the detail subbands with a threshold function to obtain \( \hat{f}_{ij} \). The denoised estimate is then \( \hat{g} = \mathcal{W}^{-1} \hat{f} \), where, \( \mathcal{W}^{-1} \) is the inverse wavelet transform.

Wavelet transform of noisy signal should be taken first and then thresholding function is applied on it. Finally the output should be undergone inverse wavelet transformation to
obtain the estimate \( \hat{f} \). There are two thresholding functions frequently used, i.e. a hard threshold and soft threshold. The hard-thresholding function keeps the input if it is larger than the threshold; otherwise, it is set to zero. It is described as:

\[
\eta_1(w) = wI(|w| > T),
\]

(2.16)

where \( w \) is a wavelet coefficient, \( T \) is the threshold and \( I(x) \) is a function the result is one when \( x \) is true and zero vice-versa. The soft-thresholding function (also called the shrinkage function) takes the argument and shrinks it toward zero by the threshold. It is described as:

\[
\eta_2(w) = (w - sgn(w)T)I(|w| > T),
\]

(2.17)

where \( sgn(x) \) is the sign of \( x \). The soft-thresholding rule is chosen over hard-thresholding, for the soft-thresholding method yields more visually pleasant images over hard-thresholding.

Figure 2.4: The Result of 2D wavelet decomposition of underwater image at level 3
Chapter 2. *An Image Based Technique for Enhancement of Underwater Images* 62

Modified BayesShrink

Wavelet shrinkage is a method of removing noise from images in wavelet shrinkage, an image is subjected to the wavelet transform, the wavelet coefficients are found, the components with coefficients below a threshold are replaced with zeros, and the image is then reconstructed [32].

In particular, the BayesShrink function has been attracting attention recently as an algorithm for setting different thresholds for every subband. Here subbands are frequently bands that differ from each other in level and direction. The BayesShrink function is effective for images including Gaussian noise. The observation model is expressed as follows: \( Y = X + V \).

Here \( Y \) is the wavelet transform of the degraded image, \( X \) is the wavelet transform of the original image, and \( V \) denotes the wavelet transform of the noise components following the Gaussian distribution \( N(0, \sigma_v^2) \). Here, since \( X \) and \( V \) are mutually independent, the variances \( \sigma_y^2, \sigma_x^2 \) and \( \sigma_v^2 \) of \( y, x \), and \( v \) are given by:

\[
\sigma_y^2 = \sigma_x^2 + \sigma_v^2. \tag{2.18}
\]

Let us present a method for deriving the noise: It has been shown that the noise standard deviation \( \sigma_v \) can be accurately estimated from the first decomposition level diagonal subband \( HH_1 \) by the robust and accurate median estimator.

\[
\hat{\sigma}_v^2 = \frac{\text{median}(|HH_1|)}{0.6745}. \tag{2.19}
\]

The variance of the degraded image can be estimated as

\[
\hat{\sigma}_y^2 = \frac{1}{M} \sum_{m=1}^{M} A_m^2, \tag{2.20}
\]

where \( A_m \) are the coefficients of wavelet in every scale, \( M \) is the total number of coefficient of wavelet.
The threshold value $T$ can be calculated using

$$T_{MBS} = \frac{\beta \hat{\sigma}_v^2}{\hat{\sigma}_x},$$

(2.21)

where $\beta = \sqrt{\frac{\log M}{2 \times J}}, \ M$ is the total of coefficients of wavelet, $j$ is the wavelet decomposition level present in the subband coefficients under scrutiny and $\hat{\sigma}_x = \sqrt{\max(\hat{\sigma}_y^2 - \hat{\sigma}_v^2)}$.

Note that in the case where $\hat{\sigma}_v^2 \geq \hat{\sigma}_y^2, \hat{\sigma}_x^2$ is taken to be zero, i.e. $T_{MBS} \rightarrow \infty$. Alternatively, in practice one may choose $T_{MBS} = \max|A_m|$, and all coefficients are set to zero.

The Modified BayesShrink thresholding technique [111] performs soft thresholding with adaptive data driven subband and level dependent near optimal threshold given by:

$$T_{MBS} = \begin{cases} \frac{\beta \hat{\sigma}_v^2}{\hat{\sigma}_x}, & \text{if } \hat{\sigma}_v^2 < \hat{\sigma}_y^2 \\ \max|A_m|, & \text{otherwise} \end{cases}$$

(2.22)

### 2.2.3 Bilateral Filtering

Bilateral filtering smooths images while preserving edges, by means of a nonlinear combination of nearby image values [133]. The idea underlying bilateral filtering is to do in the range of an image what traditional filters do in its domain. Two pixels can be close to one another, that is, occupy nearby spatial location, or they can be similar to one another, that is, have nearby values, possibly in a perceptually meaningful fashion. Closeness refers to vicinity in the domain, similarity to vicinity in the range. Traditional filtering is domain filtering, and enforces closeness by weighing pixel values with coefficients that fall off with distance. The range filtering, this averages image values with weights that decay with dissimilarity. Range filters are nonlinear because their weights depend on image intensity or color. Computationally, they are no more complex than standard non-separable filters. The combination of both domain and range filtering is termed as bilateral filtering. A low-pass domain filter to an image $f(x)$ produces an output image defined as follows:
where $c(\xi, x)$ measures the geometric closeness between the neighborhood center $x$ and a nearby point $\xi$. The bold font for $f$ and $h$ emphasis the fact that both input and output images may be multiband. If low-pass filtering is to preserve the dc component of low-pass signals we obtain

$$k_d(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, x) d\xi,$$  \hspace{1cm} (2.24)

If the filter is shift-invariant, $c(\xi, x)$ is only a function of the vector difference $\xi - x$, and $k_d$ is constant.

Range filtering is similarly defined:

$$h(x) = k_r^{-1}(x) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi) s(f(\xi), f(x)) d\xi.$$  \hspace{1cm} (2.25)

Contrary to what occurs with the closeness function $c$, the normalization for the similarity function $s$ depends on the image $f$. The similarity function $s$ is unbiased if it depends only on the difference $f(\xi) - f(x)$. The combined domain and range filtering will be denoted as bilateral filtering, which enforces both geometric and photometric locality. Combined filtering can be described as follows:

$$h(x) = k^{-1}(x) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi) c(\xi, x) s(f(\xi), f(x)) d\xi,$$  \hspace{1cm} (2.26)

with the normalization

$$k(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, x) s(f(\xi), f(x)) d\xi.$$  \hspace{1cm} (2.27)

### 2.2.4 Contrast Stretching and Color Correction

Contrast stretching often called normalization is a simple image enhancement technique that attempts to improve the contrast in an image by ‘stretching’ the range of intensity
values. The full range of pixel values that the image concerned is given by eq. (2.28). Color correction is performed by equalizing each color means. In underwater image colors are rarely balanced correctly, this processing step suppresses prominent blue or green color without taking into account absorption phenomena.

\[
I_{i,j} = \begin{cases} 
\frac{I_{i,j} - \min_I}{\max_I - \min_I}, & \text{if } 0 < I_{i,j} < 1 \\
0, & \text{if } 0 > I_{i,j} \\
1, & \text{if } 1 < I_{i,j}
\end{cases}
\]  

(2.28)

where \(\min_I\) and \(\max_I\) are the minimum and maximum intensity values in the image.

### 2.3 Experimental Results

We have conducted experiments to evaluate proposed image enhancement technique using images of our underwater image database. The captured images are suffered from non-uniform illumination of light, low contrast, blurring and typical noise levels for underwater conditions. Our technique comprises of homomorphic filtering to correct non-uniform illumination of light, wavelet denoising to remove additive Gaussian noise present in underwater images, bilateral filtering to smooth underwater image and contrast stretching to normalize the RGB values. In order to evaluate our approach, we have used PSNR, gradient magnitude and contrast value of the image and results are compared with Bazeille et al., [9] approach. The test images which are used for experimentation are shown in Figure 2.5.

The experimentation is carried out in two stages. In the first stage, we have conducted various experiments on captured images and estimated optimal filter bank and optimal wavelet shrinkage function for wavelet based image denoising. And, we also conducted experiments to estimate optimal parameters for bilateral filter for image smoothing. In the second stage, we conducted the experiments using estimated optimal filter bank, optimal wavelet shrinkage function and optimal parameter for bilateral filter for our image datasets.

The procedure involved in the first stage is as follows: after applying the homomorphic filter for correction of illumination and reflectance components, wavelet denoising is used
to remove the Gaussian noise, which is common in the underwater environment. In wavelet denoising, filter bank plays an important role for the best result of denoising. We performed an evaluation of four filter banks such as Haar, db4, Sym4 and Coif4 for decomposing the image prior to applying shrinkage function. The Table 2.1 shows the PSNRs obtained using four filter banks such as Haar, db4, Sym4 and Coif4 for each underwater image. The Coif4 filter bank yields optimal PSNR for all the underwater images.

After finding the Coif4 filter bank is the best for underwater images, we identify suitable wavelet shrinkage function by comparing and evaluating various wavelet shrinkage functions based on PSNR. We have considered BayesShrink [46], VisuShrink [29][30], Adaptive Sub-band Thresholding [32, 127, 121], NormalShrink [70] and Modified BayesShrink for comparison purpose. The Table 2.2 presents comparison results of various wavelet shrinkage functions. The experimental result shows that the Modified BayesShrink function achieves highest PSNR compared to other shrinkage functions. Hence, the wavelet based denoising technique with Modified BayesShrink function is suitable for removing the additive noise present in the underwater images. The Modified BayesShrink performs denoising that is consistent with the human visual system that is less sensitive to the presence of noise in a vicinity of image features.

We applied bilateral filter on denoised image for edge preserving smoothing that is non-iterative and simple. The bilateral filtering is performed in CIE Lab color space is the natural type of filtering for color images. To find the optimal parameter for bilateral filter, the bilateral filtering is applied to denoised images by varying the parameters $\sigma_d$ and $\sigma_r$. The interval of parameter values considered, for $\sigma_d$ is 1-10 pixel values and for $\sigma_r$ is 10-200 intensity values. The experimental results show that the parameter values $\sigma_d = 1$ and $\sigma_r = 10$ smooth the image compared to other parameter values. Hence, $\sigma_d = 1$ and $\sigma_r = 10$ are the optimal parameters for bilateral filter.

After finding optimal parameters, in the second stage of experimentation, we used Coif4 filter bank and Modified BayesShrinkage function for wavelet denoising and $\sigma_d = 1$ and $\sigma_r = 10$ for bilateral filter, which yields best results on degraded underwater images. We used the same setup to evaluate the proposed technique quantitatively as well as qualitatively. In order to evaluate qualitatively, the gradient magnitude histogram and the edge detection (canny edge detector) are computed on original images and the enhanced images. The
histograms show that gradient values are larger after enhancing compared to gradient values obtained on original images (Figure 2.8). Similarly, the edge detection results of the enhanced images demonstrate an efficiency of the proposed technique (Figure 2.7).

Apart from the perception of human vision subjectively (qualitatively), image contrast was employed to evaluate the quality of the enhanced image objectively (quantitatively). Generally, the higher the contrast value means that the clearer the image. Therefore, in order to evaluate quantitatively, we compute the contrast measurement for both original and enhanced images using the equation given below:

$$C(I) = \sqrt{\frac{1}{N} \sum_{v=1}^{N} \sum_{\chi=r,g,b} (I_{v}^{\chi} - \bar{T}^{\chi})^2} \sum_{\chi=r,g,b} \bar{T}^{\chi},$$

where $I$ is the image with $N$ pixels, $C(I)$ is the contrast. where $\chi$ is the index of the chromatic band (red, green and blue channels) and $\bar{T}^{\chi}$ is mean value, which is computed for each channel independently.

$$\bar{T}^{\chi} = \frac{1}{N} \sum_{v=1}^{N} I_{v}^{\chi}.$$  

The experiments conducted on an Intel Pentium Core i5 processor of speed 3.30 GHz and 4 GB of RAM. The image enhancement techniques were implemented and tested in MATLAB environment. The performance of our approach is compared with Bazeille et al., [9] approach based on image visual quality, computational time and contrast measurement to show the tendency of our approach. From Figure 2.9, it is observed that our approach yields better image visualization compared to Stephane Bazeille approach. The proposed technique spends 26.67 seconds whereas Bazeille et al., [9], approach spends 12.96 seconds. Even though our approach spends very high computational cost but delivers good results suitable for underwater applications. The contrast value (in percentage) is calculated between our approach and Bazeille et al., approach and Table 2.3 shows that our approach has very high contrast value for all the datasets considered.
Figure 2.5: Underwater test images

Table 2.1: The Comparison of four wavelet filter banks based on PSNR (dB)

<table>
<thead>
<tr>
<th>Image #</th>
<th>Filter Bank</th>
<th>MSE</th>
<th>PSNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image #1</td>
<td>Haar</td>
<td>0.0242</td>
<td>64.2905</td>
</tr>
<tr>
<td></td>
<td>Db4</td>
<td>0.0050</td>
<td>71.1837</td>
</tr>
<tr>
<td></td>
<td>Sym4</td>
<td>0.0059</td>
<td>70.4499</td>
</tr>
<tr>
<td></td>
<td>Coif4</td>
<td>0.0043</td>
<td>71.7861</td>
</tr>
<tr>
<td>Image #2</td>
<td>Haar</td>
<td>0.0540</td>
<td>60.8066</td>
</tr>
<tr>
<td></td>
<td>Db4</td>
<td>0.0144</td>
<td>66.5616</td>
</tr>
<tr>
<td></td>
<td>Sym4</td>
<td>0.0161</td>
<td>66.0607</td>
</tr>
<tr>
<td></td>
<td>Coif4</td>
<td>0.0128</td>
<td>67.0677</td>
</tr>
<tr>
<td>Image #3</td>
<td>Haar</td>
<td>0.1909</td>
<td>55.3232</td>
</tr>
<tr>
<td></td>
<td>Db4</td>
<td>0.2131</td>
<td>54.8456</td>
</tr>
<tr>
<td></td>
<td>Sym4</td>
<td>0.1217</td>
<td>57.2787</td>
</tr>
<tr>
<td></td>
<td>Coif4</td>
<td>0.1154</td>
<td>57.5078</td>
</tr>
<tr>
<td>Image #4</td>
<td>Haar</td>
<td>0.0744</td>
<td>59.4173</td>
</tr>
<tr>
<td></td>
<td>Db4</td>
<td>0.1129</td>
<td>57.6021</td>
</tr>
<tr>
<td></td>
<td>Sym4</td>
<td>0.0643</td>
<td>60.0509</td>
</tr>
<tr>
<td></td>
<td>Coif4</td>
<td>0.0594</td>
<td>60.3960</td>
</tr>
</tbody>
</table>

Table 2.2: The Comparison of five wavelet shrinkage functions based on PSNR (dB)

<table>
<thead>
<tr>
<th>Image #</th>
<th>Modified BayesShrink</th>
<th>BayesShrink</th>
<th>Normal Shrink</th>
<th>Adaptive Subband Thresholding</th>
<th>VisuShrink</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image #1</td>
<td>66.2116</td>
<td>66.2008</td>
<td>65.9764</td>
<td>65.0434</td>
<td>50.6137</td>
</tr>
<tr>
<td>Image #2</td>
<td>63.1458</td>
<td>63.1301</td>
<td>62.6485</td>
<td>61.6751</td>
<td>48.3258</td>
</tr>
<tr>
<td>Image #3</td>
<td>54.8456</td>
<td>54.7995</td>
<td>54.0704</td>
<td>52.1615</td>
<td>41.7070</td>
</tr>
<tr>
<td>Image #4</td>
<td>57.6021</td>
<td>57.5921</td>
<td>57.4179</td>
<td>56.6197</td>
<td>44.7697</td>
</tr>
</tbody>
</table>
Figure 2.6: First column: original image, second column: after homomorphic filtering, third column: after wavelet denoising, fourth column: after bilateral filtering, last column: after contrast equalization

Table 2.3: The Contrast of the Original image $C(I)$ and the enhanced images using our approach $C(\text{Our})$ and Bazeille et al. approach $C(\text{Ste})$

<table>
<thead>
<tr>
<th>Image #</th>
<th>Original Image $C(I)$ %</th>
<th>Our Approach $C(\text{Our})$ %</th>
<th>Bazeille et al. Approach $C(\text{Ste})$ %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image #1</td>
<td>2.58</td>
<td>5.40</td>
<td>2.34</td>
</tr>
<tr>
<td>Image #2</td>
<td>2.50</td>
<td>6.22</td>
<td>5.12</td>
</tr>
<tr>
<td>Image #3</td>
<td>2.46</td>
<td>5.75</td>
<td>1.79</td>
</tr>
<tr>
<td>Image #4</td>
<td>3.08</td>
<td>5.91</td>
<td>2.59</td>
</tr>
</tbody>
</table>
Chapter 2. *An Image Based Technique for Enhancement of Underwater Images* 70

Figure 2.7: Edge detection results on four images; First row: edge detection results on original images, Second row: edge detection results on preprocessed images

(a) Image #1  
(b) Image #2  
(c) Image #3  
(d) Image #4

Figure 2.8: Gradient magnitude histogram of the four images; Red line: the gradient magnitude histogram of the original image, Green line: the gradient magnitude histogram of the preprocessed image
2.4 Chapter Summary

In this chapter, we proposed an image preprocessing technique for enhancing the quality of degraded underwater images. The proposed technique includes four filters such as homomorphic filtering, wavelet denoising, bilateral filtering and contrast equalization, which are applied sequentially. The main contribution of this chapter is inclusion of proposed modified BayesShrink and bilateral filter for denoising and smoothing of underwater images in addition to existing other filtering techniques. We identified that \( \sigma_d = 1 \) and \( \sigma_r = 10 \) for bilateral filter, similarly, combination of coif4 filter bank and Modified BayesShrink function yields higher PSNR values. The processing time of the proposed technique is very high compared to the state-of-the-art underwater image enhancement technique. The proposed preprocessing technique enhances the quality of the degraded underwater images which are suffered from non-uniform illumination, low contrast, noise and diminished colors. The quantitative and qualitative evaluation results demonstrate improved performance of our technique.