UNDER WATER IMAGE ENHANCEMENT

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Abstract— Underwater imaging is an important research area with applications in fields such as marine biology, oceanography, and underwater exploration. However, underwater images often suffer from poor colour and contrast due to the scattering and absorption of light in water. This project proposes a method for enhancing the colour and contrast of underwater images. Our method is a single image approach that does not require specialized hardware or knowledge about the underwater conditions or scene structure. The proposed method is evaluated on a dataset of underwater images, and the results show that it significantly improves the visual quality of the images.

I. INTRODUCTION

Underwater imaging is a challenging task due to the scattering and absorption of light in water. The resulting images often suffer from poor colour and contrast, which can make it difficult to extract meaningful information from them. This problem is especially relevant in fields such as marine biology, oceanography, and underwater exploration, where accurate and detailed imaging is crucial. Several methods have been proposed to enhance underwater images, including image restoration, colour correction, and fusion. For an ideal transmission medium, the 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 like the interaction between the sun light and the sea surface, which 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 where the 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. Underwater images are also blurred and distorted due to scattering of light between object and camera, underwater noise, absorption, colour-cast, non-uniform illumination and shading. We would propose an algorithm to enhance the quality of underwater images by removing the distortion caused due to underwater haze, colour-cast and also identify the objects from the distorted underwater images. The project contributes to the field of underwater imaging by providing a practical and efficient method for enhancing the quality of underwater images[1].

II. EXISTING IMAGE ENHANCEMENT METHODS :

A. Gamma Correction

Gamma correction is an image processing technique used to adjust the brightness and contrast of images. It is based on a non-linear mapping function that relates the input pixel intensity to the output pixel intensity. Where s is the output pixel intensity, r is the input pixel intensity, gamma is the gamma value, and c is a scaling constant. In this formula, the input image is first normalized so that the pixel intensities lie between 0 and 1. Then, gamma correction is applied to each pixel intensity value by raising it to the power of gamma. Finally, the resulting pixel intensities are scaled by a constant c to map them back to the range of 0 to 255 (or the maximum pixel value of the image). The gamma correction formula is given by

$$s = c\, r^{\gamma} \quad (1)$$

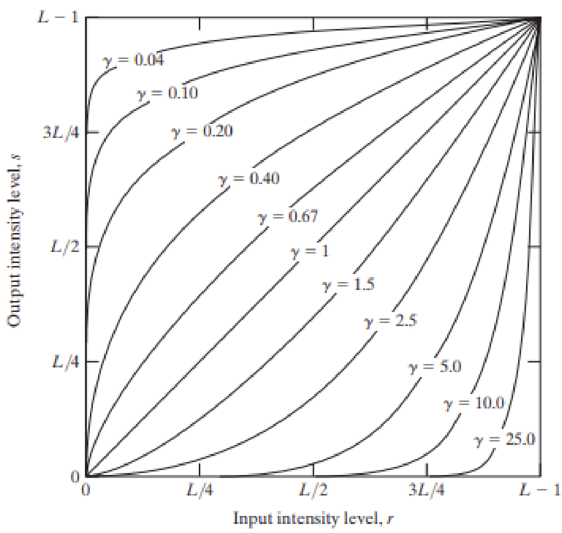
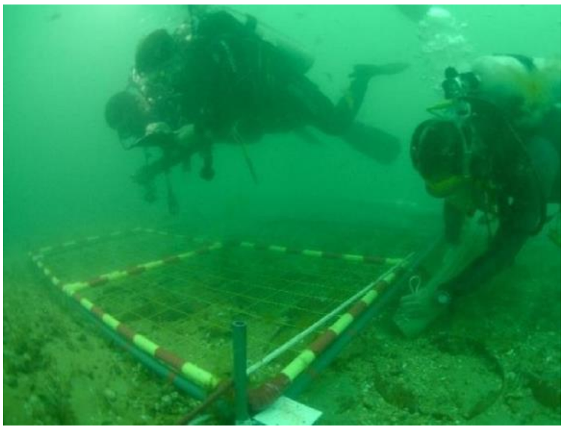


Fig. 1 Plots of the equation $s = c\, r^{\gamma}$ for various values of γ.

The value of gamma determines how the image is transformed. A value of gamma less than 1 will brighten the image, while a value of gamma greater than 1 will darken the image. A gamma value of 1 result in no change to the image. The value of gamma is typically chosen based on the characteristics of the input image and the desired output. The below plot shows how output image looks like for different values of gamma. Gamma correction is important because it allows us to adjust the brightness and contrast of images to make them more visually appealing. In particular, it can be used to correct images that are too dark or too bright, or to adjust the contrast of an image to make it more visually striking. Gamma correction is also used in the calibration of displays to ensure that images are displayed correctly and with accurate colours [2]. When Gamma = 0.9, we see image is darkened and when Gamma = 1.1, we see brighter image.



[a]

[b]

[c]

Fig. 2 Gamma Transformation. [a] Input Image [b] shows the Gamma Transformed image with gamma set to 0.9.[c] shows the Gamma Transformed image with gamma set to 1.1.

B. Histogram Equalization:

Histogram equalization is a technique used to adjust the contrast of an image by modifying its histogram. The basic idea is to redistribute the pixel intensities of an image so that they are more evenly distributed across the entire intensity range. This results in an image with increased contrast and detail. The histogram of an image is a plot of the frequency of occurrence of each pixel intensity level. It can be represented as a discrete function h(r), where r is the pixel intensity level and h(r) is the number of pixels in the image with intensity level r. The cumulative distribution function (CDF) of the image is given by:

$$CDF(r) = (L-1)\int_0^r p_r(w)dw \quad (2)$$

where CDF(r) is the cumulative distribution function at intensity level r. The CDF gives the cumulative probability of all the pixels in the image with intensity levels less than or equal to r.
Histogram equalization is achieved by transforming the pixel intensities of the image such that the resulting histogram is as flat as possible. This is done by mapping the input pixel intensities r to output pixel intensities s using the formula:

$$s = T(r) = (L-1)\int_0^r p_r(w)dw \quad (3)$$

Where L is the number of possible intensity levels in the image (typically 256 for an 8-bit image), CDF(r) is the cumulative distribution function at intensity level r and w is the dummy variable for integration.
The transformed image has a more uniform distribution of pixel intensities, resulting in improved contrast and detail. We display the distribution after histogram equalization below. However, histogram equalization can also result in an artificial appearance of the image, with unnatural colours and artifacts in some cases.

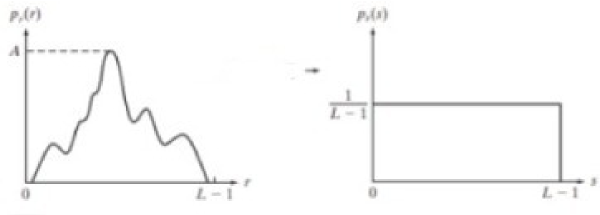
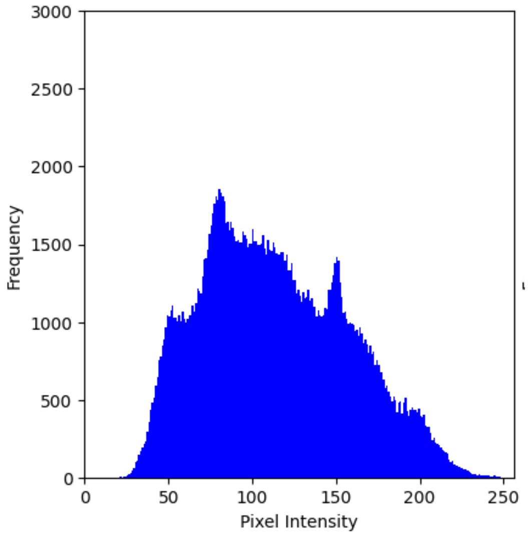


Fig. 3 We show results of applying transformation to all intensity levels r. The resulting intensities s, have a uniform PDF independently of the form of PDF of the r's.

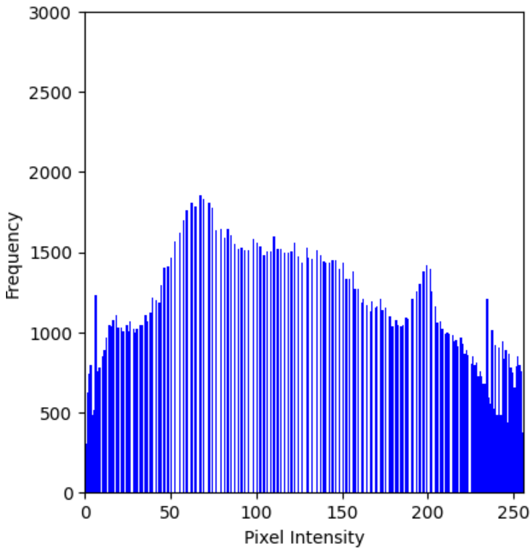
Histogram equalization is a widely used technique in digital image processing, especially in the fields of computer vision, medical imaging, and remote sensing. It is particularly useful for enhancing the contrast of low-contrast images, such as those captured under poor lighting conditions or with low-quality cameras. Histogram equalization is a method of contrast enhancement in which the intensities of an image are redistributed to make the image appear more uniform. From the displayed results, we can observe that the contrast in the histogram equalized image is improved as compared to the original image. This is because the histogram equalization process has redistributed the pixel intensities of the original image to increase the number of pixels with medium intensities, resulting in a wider range of intensities in the equalized image. The histograms of the original image and the equalized image show the distribution of pixel intensities in each image. The histogram of the equalized image has a more uniform distribution than the histogram of the original image, which indicates that the histogram equalization process has successfully increased the contrast and improved the visual appearance of the image [3].

[a]



[b]

[c]



[d]

Fig.4 Histogram Equalization. [a] is the Input image, [b] shows the histogram of the Input image, [c] shows the Histogram equalized image, [d] shows the Histogram of the histogram Equalized image.

C. White Balancing From Grey World Algorithm:

The Grey World algorithm is a popular method used for colour constancy and white balancing in digital image processing. The algorithm works under the assumption that the average colour in a scene is Grey, and uses this information to balance the colours in the image. The basic idea behind the algorithm is that if the average colour of an image is shifted towards one colour channel (i.e., red, green, or blue), then the colours in the image will appear unbalanced. By shifting the colour balance of the image towards the opposite direction, the colours can be balanced. To apply the Grey World algorithm, the average colour of the image is first calculated. This can be done by taking the mean value of the red, green, and blue colour channels across the entire image. Next, the algorithm calculates the average colour of the image as a grey colour by averaging the red, green, and blue values of the average colour. Finally, the algorithm applies a colour shift to the image by scaling the red, green, and blue colour channels such that the average colour of the image matches the grey colour calculated in the previous step. Specifically, the algorithm multiplies each colour channel by a scaling factor that is equal to the inverse of the average colour intensity [4].

$$C = \frac{c[\max(R_{avg}, B_{avg}, G_{avg})]}{C_{avg}} \tag{4}$$

Here C is the new red blue or green colour channel c is the respective red blue or green colour channel C_{avg} is the average of the red ble and green colour channel R_{avg}, B_{avg} and G_{avg} are the average of the Red blue and Green colour channels.

[a]

[b]

Fig. 5 Grey World Algorithm. [a] shows the input image [b]shows the image after applying Grey World Algorithm on the Initial image.

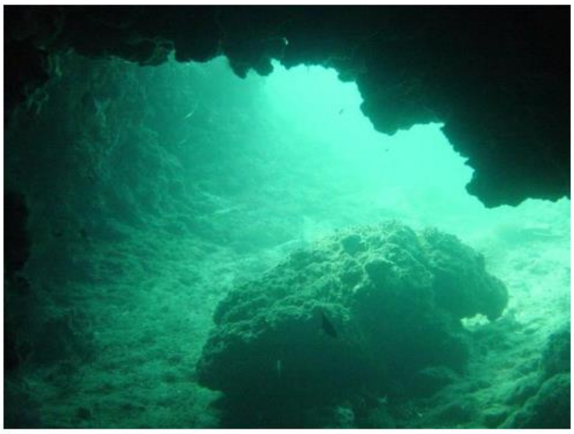
D. White Balancing

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 traveling in clear water The green channel is the one that contains opponent colour 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. The compensation should be proportional to the difference between the mean green and the mean red values

$$Irc(x) = Ir(x) + \alpha\,(Ig - Ir)(1 - Ir(x))Ig(x) \quad (5)$$

$$Ibc(x) = Ib(x) + \alpha\,(Ig - Ib)(1 - Ib(x))Ig(x) \quad (6)$$

Here Irc and Ibc is the compensated red and blue channel. Ir(x), Ib(x) and Ig(x) is the normalized values of red , blue and green channel Ig , Ib and Ir are the mean values of the green blue and red channels. Here α denotes a constant parameter and we can vary alpha to get different results [5].



[a]

[b]

[c]

Fig. 6 White Balancing. [a] shows the input image, [b] shows the colour compensated image of the input image with α set to 3, [c] shows the colour compensated image of the original image with α set to 5

E. Dark Channel Prior

Dark Channel Prior is a powerful image processing technique that is widely used for various computer vision applications such as image dehazing, object recognition, and image enhancement. It is a simple yet effective approach that can be used to estimate the depth information and remove the haze from images. The basic idea behind Dark Channel Prior is to exploit the statistical regularity of the dark pixels in an image, which are usually caused by the presence of haze or fog. In a hazy image, the pixels in the underwater objects tend to have a lower intensity than the corresponding pixels in clear images. This is because the haze attenuates the light and reduces the contrast of the image. The dark channel prior approach involves computing the minimum pixel value of each local patch in an image. This minimum value is known as the dark channel and represents the amount of haze in the patch. The dark channel can be computed efficiently using a sliding window approach, where the minimum value is computed for each window of pixels in the image [6].

Once the dark channel is computed, it can be used to estimate the transmission map of the image, which represents the amount of haze or fog in each pixel. This can be done by assuming that the ratio between the dark channel and the corresponding pixel value is proportional to the transmission. This approach works well in practice because the dark channel tends to have high contrast and low noise, which makes it a reliable indicator of the presence of haze. The transmission map can then be used to remove the haze from the image. This can be done by applying a simple dehazing algorithm, such as the atmospheric scattering model, which models the attenuation of light by the haze. The dehazed image can then be enhanced using various image processing techniques, such as contrast stretching, colour correction, and sharpening. Overall, Dark Channel Prior is a simple yet effective approach for image dehazing and other computer vision applications. It exploits the statistical regularity of dark pixels in hazy images to estimate the transmission map and remove the haze. This approach has been widely used in various applications and has been shown to achieve state-of-the-art results in many cases.

$$J(x) = \min \{\min\{y\in\Omega(x)\}[\min\{c\in\{R,G,B\}\} I_c(y)] \} \tag{7}$$

Where J(x) is the value of the dark channel at pixel x, $I_c(y)$ is the intensity of colour channel c at pixel y, and $\Omega(x)$ is a local patch around pixel x [7].

III. PROPOSED WORK

Analysis of Underwater Images

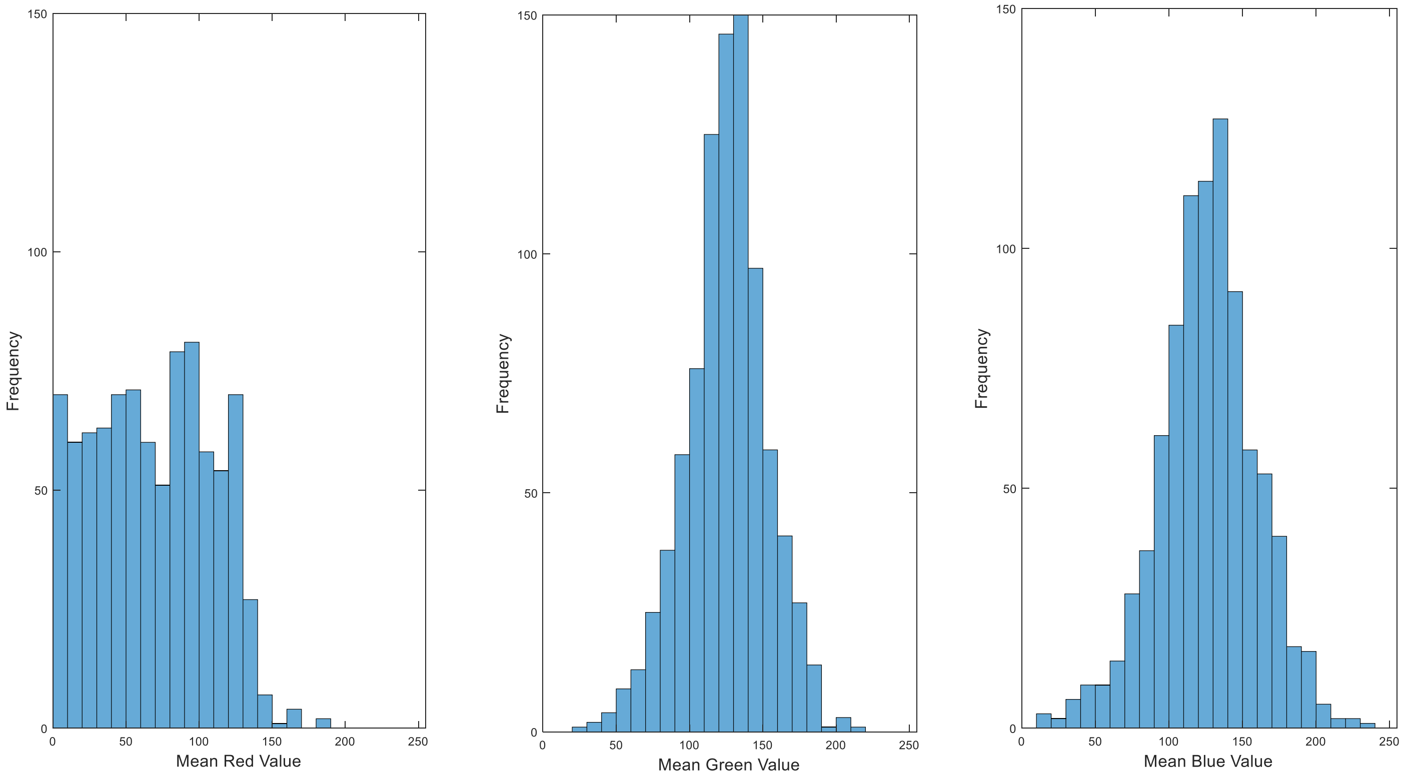
A. Histogram

Histograms are used to represent the distribution of pixel intensities in an image, and the mean values of the red, green, and blue channels provide a quantitative measure of the overall brightness of the image and the balance of colors. We draw histograms of underwater images by extracting their red, green and blue channels to check the differences between the intensity levels of red, green and blue colour between normal images and underwater images

The histograms of the red, green, and blue (RGB) color channels of a normal image and an underwater image can look significantly different. Here are some general observations about the potential differences:

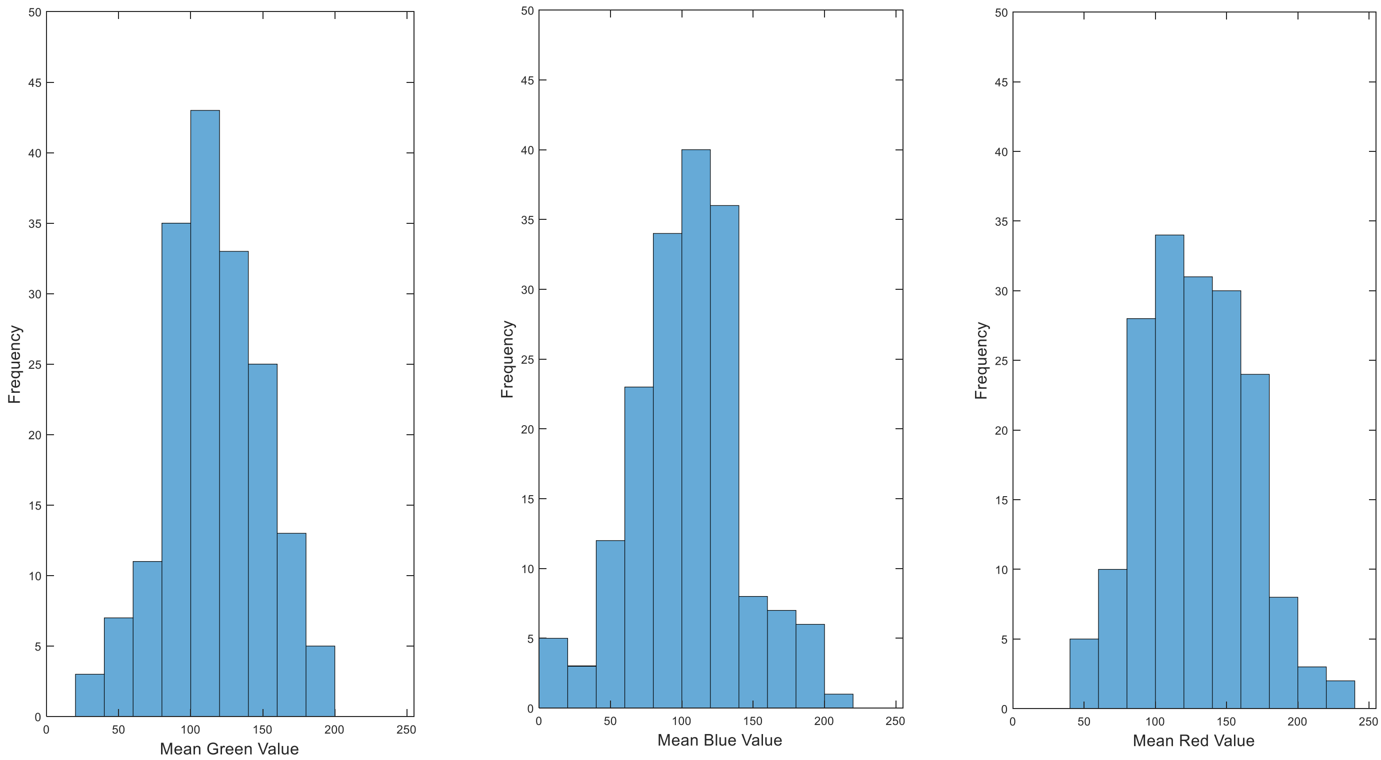
- Normal images typically have a balanced distribution of color intensities across all RGB channels. This means that the histogram for each channel will have a relatively uniform shape, with no dominant peaks or valleys.
- Underwater images, on the other hand, are often affected by water's absorption and scattering of light, which can result in significant color distortions. Depending on the depth, water quality, and lighting conditions, underwater images can have a strong color cast or appear monochromatic. Therefore, the histograms of the RGB channels for an underwater image may have irregular shapes and pronounced peaks or valleys.
- In underwater images, the green channel may have a higher intensity compared to the other two channels, and could show a dominant peak as it is relatively well-preserved underwater compared to the red and blue channels.
- Also, in turbid waters or areas with a high concentration of plankton, the blue channel may show a lower intensity due to significant attenuation caused by absorption from organic matter.
- The red channel histogram may show a low intensity in an underwater image compared to a normal image. This is because red light is absorbed quickly in water, and it has a shorter range than other colors.

In summary, the histograms of RGB channels in underwater images will be different from normal images due to the color distortions caused by water.



[a] [b] [c]

Fig. 7 [a] Shows the mean red values of underwater images vs it's frequency through bar plot. [b] Shows the mean green value of underwater images vs it's frequency through bar plot. [c] Shows the mean blue value of underwater images vs it's frequency through bar plot.

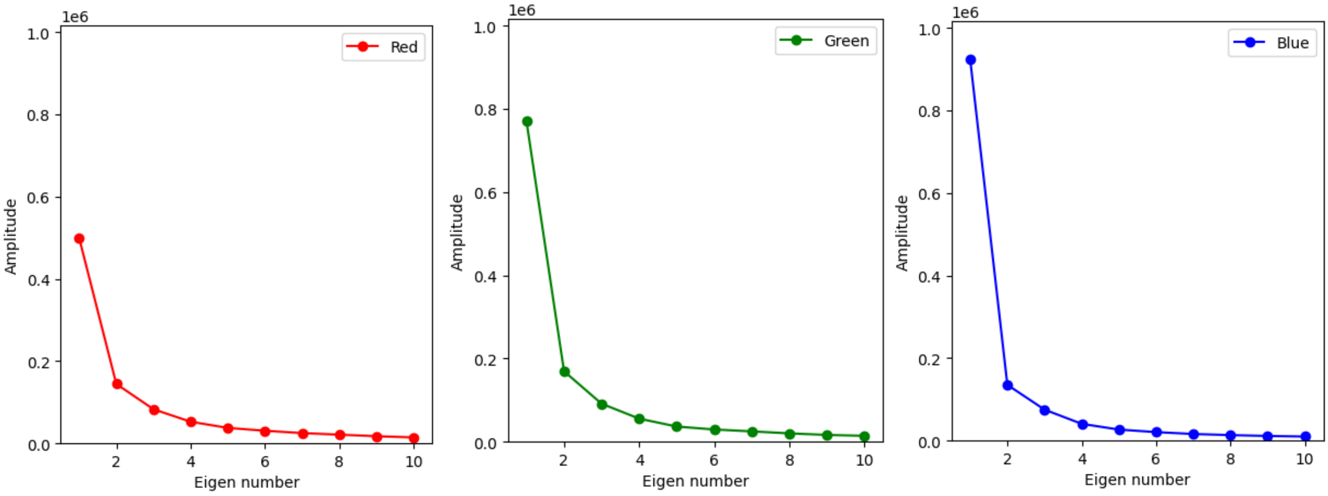


[a] [b] [c]

Fig. 8 [a] Shows the mean red values of underwater images vs it's frequency through bar plot. [b] Shows the mean green value of underwater images vs it's frequency through bar plot. [c] Shows the mean blue value of underwater images vs it's frequency through bar plot.

B. EIGEN VALUES

We aim to extract the top 10 eigenvalues from the R, G, and B channels of all images in the directory. We begin by looping all images one by one, importing an image and converting it into a matrix form. Next, we extract the R, G, and B channels and calculate the covariance matrices for each of these channels. We then compute the eigenvalues and eigenvectors for each of the covariance matrices and sort the eigenvalues in descending order. Finally, we extract the top 10 eigenvalues from each channel and reconstruct the image using the corresponding eigenvectors. The resulting image will be a reduced dimension version of the original image, retaining the most significant features of each colour channel. The proposed method can be used for image compression and feature extraction purposes.



[a] [b] [c]

Fig.9 Eigen values. [a] shows the top ten Eigen values of Red Channel, [b] shows the top ten Eigen values of Green Channel, [c] shows the top ten Eigen values of Blue Channel

Fig. 9[a] shows the average eigenvalues for the red colour channel. The plot shows that the first few eigenvalues have a much higher amplitude than the rest, indicating that these eigenvalues capture most of the variability in the data. The amplitude then decreases sharply, indicating that the remaining eigenvalues capture less variability. The second plot shows the top 10 eigenvalues for the green colour channel. The plot shows that the first eigenvalue has a much higher amplitude than the rest, indicating that this eigenvalue captures most of the variability in the data. The amplitude then decreases sharply for the second eigenvalue, indicating that this eigenvalue captures much less variability than the first. The remaining eigenvalues have a similar amplitude and capture even less variability. The third plot shows the average eigenvalues for the blue colour channel. The plot shows a similar pattern to the first plot, where the first few eigenvalues have a much higher amplitude than the rest, indicating that these eigenvalues capture most of the variability in the data. The amplitude then decreases sharply, indicating that the remaining eigenvalues capture less variability.

The output plots show that the blue channel has the highest eigenvalues on average, followed by Green and then Red. This observation is consistent with the way light behaves in water, as water absorbs light differently depending on the wavelength. In particular, the blue light is absorbed least by water, while the green light is absorbed more, and the red light is absorbed most. This means that the blue channel in underwater images can capture more information and detail, hence leading to higher eigenvalues on average compared to the other colour channels. Overall, the plots demonstrate the importance of understanding the distribution of data in different channels for effective image processing [8].

C. Image Reconstruction From Eigenvalues

Principal Component Analysis (PCA) is a popular technique for dimensionality reduction and feature extraction in digital image processing. PCA works by identifying the most significant modes of variation in a set of images, and representing each image as a linear combination of these modes. This can be useful for reducing the storage requirements of an image, extracting features for image classification, and enhancing image contrast. PCA starts by collecting a set of training images, which are represented as high-dimensional vectors. These vectors can be standardized by subtracting the mean image vector Mx, and then transformed using the matrix A, which is computed from the eigenvectors of the covariance matrix. The matrix a represents the directions of maximum variation in the data, and the transformed vectors y represent the images in a new coordinate system aligned with these directions. This transformation can be expressed using the formula y=A(x-Mx), where x is the matrix of standardized image vectors. The covariance matrix of the transformed vectors y is then computed as

$$C_y=AC_xA^T \quad (8)$$

where C is the matrix of eigenvalues and at is the transpose of the matrix A. The eigenvectors and eigenvalues of C_y can be calculated to obtain the eigen image basis. The matrix a can be truncated to include only the eigenvectors with the highest eigenvalues, as these correspond to the most significant modes of variation in the image data. Its known as Hoteling transform.

To reconstruct an image from its coefficients in the eigen image basis, the inverse transformation can be applied using the formula

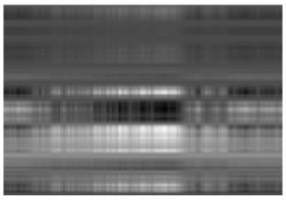
$$x=A^T y + M_x. \quad (9)$$

The coefficients can be computed using the formula

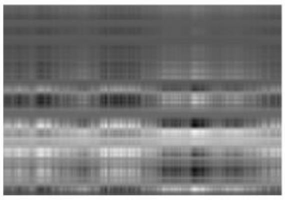
$$c=A^T(y-M_x) \quad (10)$$

where y is the matrix of transformed image vectors. The resulting coefficients can be used for various image processing tasks, such as image compression, feature extraction, and image enhancement. For example, image compression can be achieved by discarding the least significant coefficients and quantizing the remaining coefficients. Image enhancement can be achieved by filtering the coefficients to remove noise or enhance image contrast. Overall, PCA is a powerful technique in digital image processing that can be used for dimensionality reduction, feature extraction, and image enhancement. The transformation using the matrix a and the inverse transformation using the transpose of a can be used to compute the eigen image basis and the corresponding coefficients, which can be used for a wide range of image processing tasks [9].

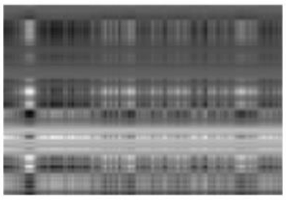
[a]



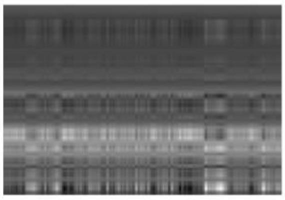
[b]



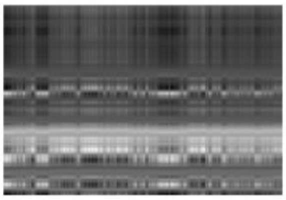
[c]



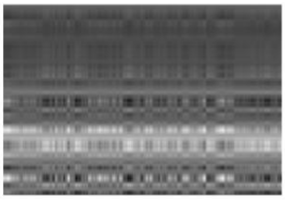
[d]



[e]



[f]



[g]

Fig. 11 [a] shows Input image, [b] shows 1 Principal Component, [c] shows Principal Component 2, [d] shows Principal Component 3,[e] shows Principal Component 4,[f] shows Principal Component 5 and [g] shows Six Principal Component 6.

We load an image and convert it to grayscale and then center the image by subtracting the mean of each row from the corresponding row. The covariance matrix of the centered image is then computed. The eigenvectors and eigenvalues of the covariance matrix are computed and sorted in descending order of eigenvalues. The top 6 eigenvectors are then selected and used to compute the projection matrix. The top 6 principal component images are then reconstructed using the projection matrix and displayed. The top 6 principal component images represent the directions of greatest variation in the image dataset. They can be used to reduce the dimensionality of the image dataset while preserving the most important information. By plotting these images, we can visualize the structure of the dataset and gain insights into its underlying patterns. The original image is also displayed for comparison. One observation from the output is that the top principal component images represent the most dominant patterns present in the input image. The first principal component image represents the overall brightness of the image, while the subsequent components capture more specific patterns such as edges and textures. It is also important to note that the reconstructed images may not exactly match the original image due to the loss of information during dimensionality reduction. The quality of the reconstruction can be improved by using more principal components or by optimizing the selection of principal components based on the reconstruction

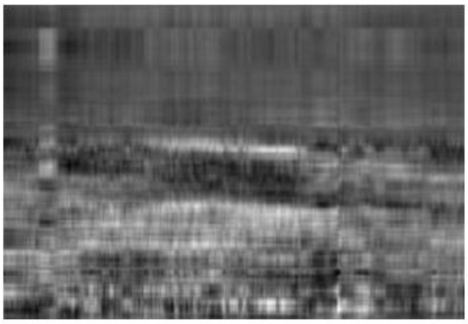


Fig. 12 It shows the reconstructed image

We reconstruct original image by using the top 6 principal components. First, the input image is converted to grayscale and centered by subtracting the mean of each row. Then, covariance matrix is computed using the centered image. The eigenvectors are sorted by decreasing eigenvalues. The top 6 eigenvectors are selected and used to compute the projection matrix. The original image is reconstructed using the projection matrix and the centered image. The reconstructed image is plotted alongside the original image for comparison. From the reconstructed image, we can observe that the general structure of the original image is preserved, but the image appears somewhat blurry. This is because we are only using the top 6 principal components to reconstruct the image, which is a relatively small number. Using more principal components would result in a higher fidelity reconstruction, but also a larger amount of data to store and transmit. The trade-off between reconstruction quality and data storage/transmission is an important consideration in applications of PCA [10].

IV. SUMMARY

We applied various existing image enhancement methods like Gamma Correction, Histogram Equalization, White Balancing using grey world method and colour compensation method. For Gamma Correction, when we took γ less than 1 , we notice brighter images, and for γ greater than 1, we notice darker images. In histogram equalization, we notice contrast enhancement of the histogram equalized image as its histogram now is uniformly distributed. We tried two different method for white balancing in Grey world method we observed that the dominance of the green channel is reduced and over all colour balance improved and in colour compensation method of white balancing we observed that the dominance of green colour is reduced but if we increase the value of α the blue colour started dominating the image We have analyzed Histogram of mean red green and blue values of underwater and normal images and noticed that there is a severe loss of intensity for red channel. We also extracted eigen values for Top 10 red, green and blue channels for underwater Images and noticed that red channel had lowest eigen values. We also performed Image reconstruction of underwater image using eigen values and since we used only top 6 Principal components, the reconstructed image appeared blurry.

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