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Framework for Underwater Image Enhancement

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Abstract

In this paper, we propose a framework for enhancement of underwater images. Underwater images suffer from low-contrast, blur and non-uniform illumination resulting in poor quality images. Red color in the atmospheric light is absorbed early due to its shorter wavelength, whereas the colors like blue and green penetrate deeper into water due to larger wavelength. As a result the underwater images appear bluish or greenish in color. Towards this, we propose a framework for enhancement of underwater images using color balance and Laplacian and Gaussian fusion pyramid. Here we aim to balance the color distribution of the underwater image in LAB color space, to remove the bluish-green tint caused due to atmospheric light attenuation. Focus is on sharpening the underwater image to enhance the edges distorted during the process of color balance. We emphasize on fusion of outputs obtained after color balancing and edge sharpening. We demonstrate the performance of the proposed framework using qualitative evaluation metrics and show, the results obtained through the proposed fusion framework outperforms the state of art enhancement methods. The proposed approach can also be used for enhancement of other kind of images like foggy or hazy on ground images.

Keywords: Underwater Image; Image Enhancement; Color Balance; Image Fusion.

Fig. 1. Results of proposed framework; First row shows the input underwater images, and the second row shows the corresponding outputs.

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1. Introduction

Underwater photography has gained a major interest specifically for understanding the ancient culture and history through the submerged archaeological sites. In spite of the large imaging techniques available underwater images still suffer from low-contrast, blur and non-uniform illumination resulting in poor quality images [11]. Beneath the surface of water are many micro-organisms,Phytoplankton's, disastrous wrecks of ships,monuments and there deposits submerged. Capturing of such underwater scene is a major challenge as image formation underwater is subjective to the environmental conditions.

Underwater image quality improvement is addressed using enhancement and restoration frameworks. Enhancement of underwater images has gained a leap as, underwater images are degraded due to light attenuation, back-scattering and distortion of light. Different techniques have been proposed to improve the quality of underwater images, right from simple color correction to deep learning methods. Unlike image enhancement, restoration is an objective process and we tend to recover naturally degraded image. Typically underwater image restoration is sensitive to the parameters like climatic conditions, time of the day, depth of water, type of sea bed, phytoplanktons, dominant organic matter(DOM), atmospheric light and back scattered light. Authors in [16] [12] estimate atmospheric light on single image using adaptive filters and color models.

Early imaging techniques were dependent on underlying hardware and were quite expensive. Recent enhancement techniques are based on single image [3] [1]and are dataset dependent. Authors in [2] propose a method to estimate back-scattered light locally and globally using neighborhood of the pixels. Back scattering of light introduces haze in an underwater image and affects the visibility. Authors in [7] [5] [3] discuss underwater image dehazing approach using the statistics of hazy image. Authors in [8] discuss an approach to dehaze an image by using haze lines with an assumption that haze free image has tight RGB clusters whereas hazed images have scattered distribution of RGB clusters. Authors in [10] discuss about dehazing an image using color lines.

The typical approach to generate more informative image is by combining multiple observations of the same scene. As per the sampling theorem, higher sampling density ensures better reconstruction. The spatial and spectral resolution of a monocular imaging system limits the information in single image. Hierarchical (Multi-scale) framework based image fusion techniques [6] generate visual quality with spectral information [13] [14] [15]. Authors in [4] discuss multi-scale fusion technique with white balancing towards underwater image enhancement. We observe, white balancing of underwater image introduces color distortion, and appears to have lost its originality.

We consider image fusion approach with the perspective of fusing images obtained across multiple processes as shown in Figure 2. This approach of fusion may facilitate better machine and human perception. The purpose to imbibe such a process is to infer more features suppressed during image acquisition process. Many fusion techniques are available, however applying the same towards underwater image enhancement is a novel approach towards inferring more features from single image.

Towards this,

- We propose a framework for underwater image enhancement with image fusion and color balance towards retaining the originality in enhanced underwater image. We include
  - Filtering and weighted based color balance of the RGB color channels in LAB color space.
  - White balance of underwater image which results in smoothened edges.
  - Sharpening of edges using guided filter.
  - Mutli-scale fusion using Laplacian and Gaussian pyramid to fuse the outputs of the color balance and sharpening blocks to get the enhanced output.
- We demonstrate the results of the proposed framework using benchmark dataset, compare the results with state of art methods.

2. Framework for Enhancement of Underwater Images

The proposed framework is as shown in Figure 2. We perform simplest color balance on the underwater image to balance the distribution of the colors across the color space, in order to address bluish-green haze in the image. Due to the presence of water effect, blur is seen even after color balance. To address this we perform, Contrast Limited

Adaptive Histogram Equalization(CLAHE) on L channel in LAB color space for the color balanced image to remove water effect. High frequency details in the image are suppressed during CLAHE, to address this we sharpen the edges in the image using guided filter. This provides better visualization and machine/human perception towards underwater image. We propose to fuse the image obtained after CLAHE with sharpened image by multi-scale decomposition based on Laplacian pyramid, towards obtaining an enhanced underwater image. The fusion helps in regularizing the image features for reconstructing enhanced underwater image.

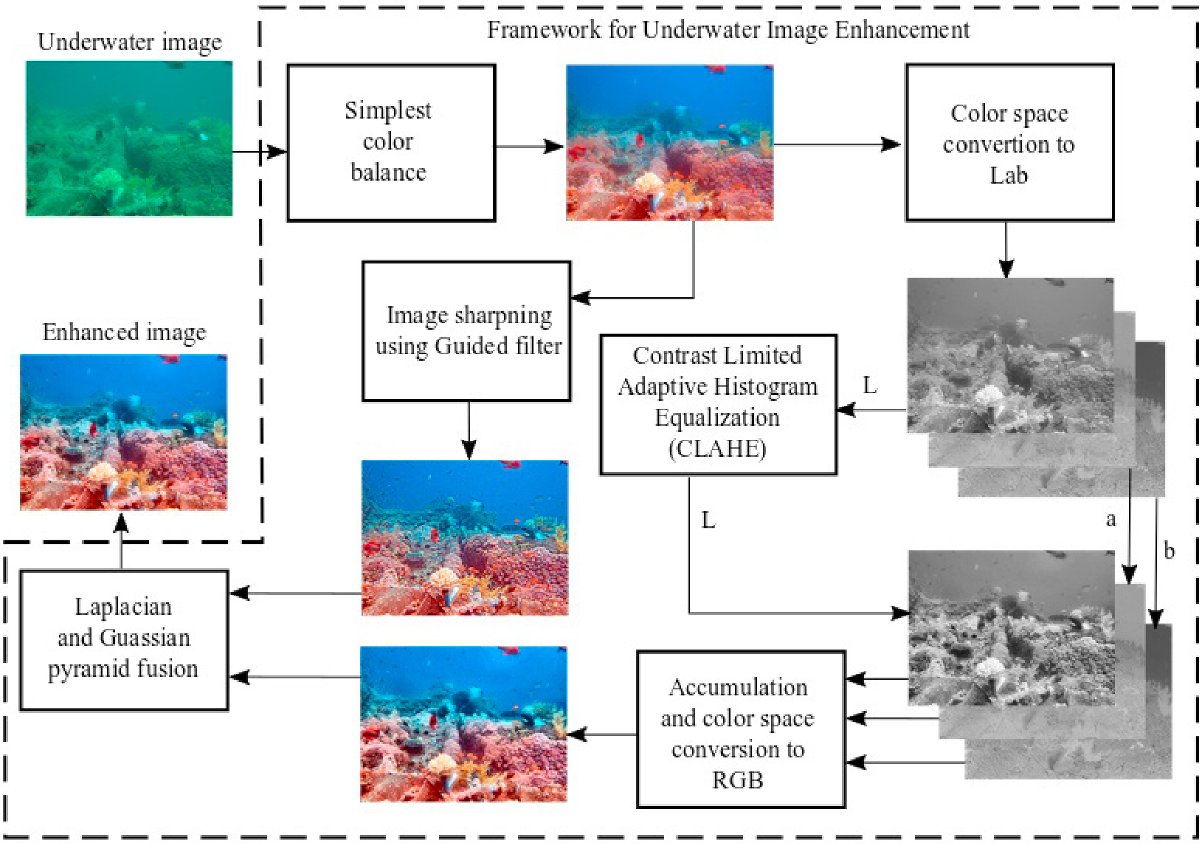


Fig. 2. Framework for Underwater Image Enhancement

2.1. Simplest Color Balance

Simplest color balance is a process of removing bluish-green haze introduced due to dominant organic matter during data acquisition. The objective is to transform the acquired colors to more appropriate from. This process is carried out so as to bridge the gap between acquisition sensors and human visual perception. Towards this we perform overall adjustment of intensities of colors in the image. There are numerous methods proposed for color balance like sorting method and histogram method. Among these methods we have applied histogram method for color balance as proposed in [4]. According to the algorithm we perform a color balance on the image data where we consider $n1\%$ of the pixels saturated on the minimal side of the density distribution in the histogram, and $n2\%$ percentage of pixels on the maximal side of the density distribution in the histogram. For example, if $n1 = 0$ then, no pixels are considered in the range of $[0, V_{min}]$, and if $n2 = 3$ then, 3 percent of no of pixels(N) are considered in the range $[V_{max}, 255]$.

Towards this,

1. We build a cumulative histogram of the pixel values. Let the total number of pixels in the image be N. Let V_{min} be the lowest histogram label i.e. the minimum pixel value of the input image to be considered and V_{max} be the highest histogram label i.e. the maximum pixel value of the input image to be considered. To build the cumulative histogram we use the following equations:
   $hist[image[i]] := hist[image[i]] + 1$, for i in the range of [0, N-1]
   $hist[i] := hist[i] + hist[i1]$, for i in range of [1,255]
2. We divide the pixel values into three quartiles $[0, V_{min}]$, $[V_{min}, V_{max}]$ and $[V_{max}, 255]$. Let $n1$ and $n2$ be the number of pixels at two extreme levels where $n1$ $[0, V_{min}]$ and $n2$ in $[V_{max}, 255]$.
3. The pixels lower than V_{min} i.e. $n1$ are updated to V_{min} and pixels values higher than V_{max} i.e. $n2$ are updated to V_{max}.
4. The image is scaled to $[min, max]$ with a transformation of the pixel values by the function $f(x)$ such that,
   $f(x) = (x - V_{min}) * (max - min)/(V_{max} - V_{min}) + min.$

2.2. Contrast Limited Adaptive Histogram Equalization

CLAHE is a generalized model for adaptive histogram equalization and differs in contrast limiting. In CLAHE, histogram of extracted luminance distribution from LAB color space is clipped based on the specified clip limit. The clip limits define the amount of noise in the histogram assisting the measure of contrast enhancement. Enhancement through CLAHE demands color balanced images, to eliminate blue-green tint in the enhanced image.

Towards this,

1. Model the RGB image to LAB color space towards extraction of Luminance component of the image.
2. Perform contrast limited adaptive histogram equalization on the extracted L component.
3. Accumulate the CLAHE equalize L component with a and b component of non equalized image.

Luminance component in LAB space closely matches with human perception of lightness, hence can be used for accurate color balance corrections and adjust the lightness contrast.

2.3. Image Sharpening using Guided Filter

High frequency components in underwater images are suppressed during color balancing. Guided filters facilitates retaining high frequency components, and is considered to be one of the fastest and efficient edge preserving and smoothing filters. We apply fast guided filter on simplest color balanced image as shown in Figure 3.

2.4. Laplacian and Gaussian Pyramid Fusion

Pyramid fusion focuses on constructing an image using the prominent features in the input images for better visual perception. An image pyramid represents pattern information at different scale and each level of pyramid captures the features with a different perception compared to the other. Fusion of CLAHE and sharpening block generated images is performed using Laplacian and Gaussian pyramid fusion technique.

Towards fusion

1. Consider Laplacian contrast weight and Local contrast weight of the two images in LAB color space.
2. Generate saliency weights of the two images in RGB color space.
3. Compute exposure as a weight in LAB color space.
4. Normalize the weights W_1 and W_2 of CLAHE and sharpened image respectively.
5. Obtain the Gaussian pyramids G_1 and G_2 using the two normalized weights of each level considering 5 levels in pyramid.
6. Obtain the Laplacian pyramids R_1, G_1, B_1 and R_2, G_2, B_2 channels for the CLAHE and sharpened images respectively for each level of pyramid.

7. Perform weighted fusion at each level for individual channels,

$$I_{py}^{(i)} = W_1^{(i)} .* I_1^{(i)(j)} + W_2^{(i)} .* I_2^{(i)(j)}$$

where $I_{py}^{(i)}$ is the fused image in i_{th} level of pyramid, and j indicates the channel.

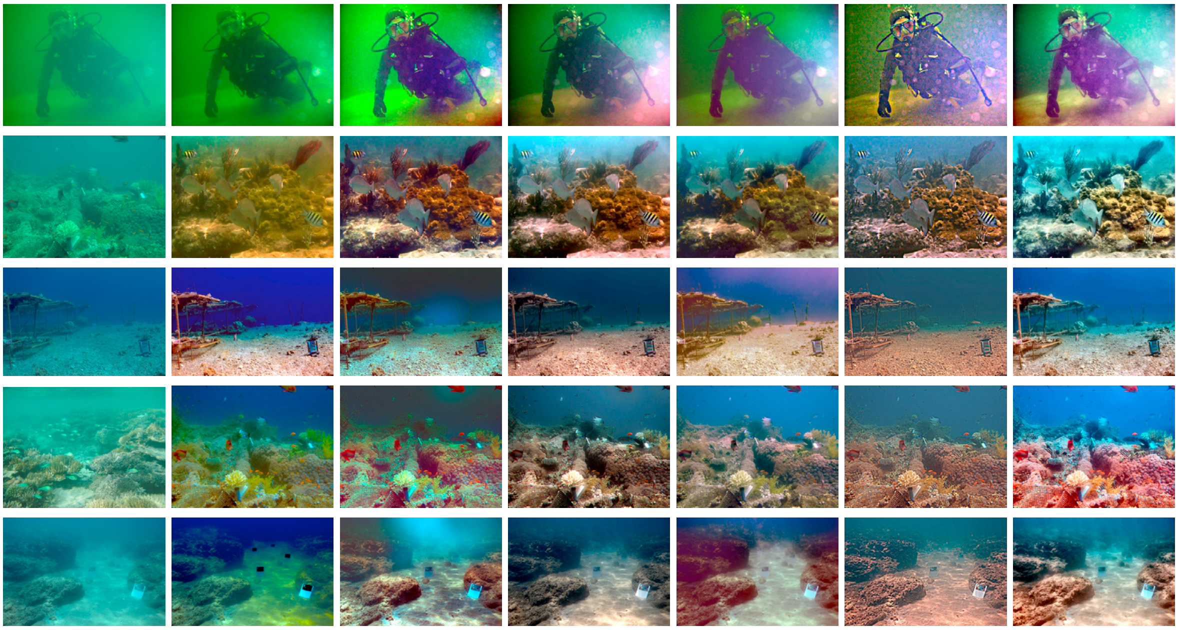
3. Results and Discussions

In this section we demonstrate the results of proposed framework. We illustrate our results through simplest color balance as shown in column (b) of Figure 3. Data captured underwater using different sensors in uncontrolled condition like diffrent depths, water types, atmospheric light leads to loss of originality in the color. Typically color balance is performed to retain the originality of the color in underwater image. CLAHE is applied to color balanced image to limit the contrast of the image lost during color balancing process. Column (c) of Figure 3 shows results obtained after adaptive histogram equalization depending on the contrast. High frequency components are suppressed after equalization, towards this image sharpening using guided filter is performed as shown in Figure 3 column (d). Fusion of sharpened image and equalized image is performed to retain high frequency components and originality of color as depicted in column (e) of Figure 3.

(a) (b) (c) (d) (e)

Fig. 3. Results of the proposed framework shown at every stage, (a) Input underwater image; Output after (b) Simplest color balance, (c) CLAHE, (d) Guided filter, (e) Fusion of output of CLAHE and guided filter.

Enhancement of an image is subjective in nature and varies from person to person. Towards this we compare our results qualitatively with state of art techniques available. Randomly drawn 100 samples were examined for qualitative analysis of the obtained result. Among 100 samples drawn, 20 percent opined enhanced image as proposed by Ancuti's method is better as shown in column (d) of Figure 4 appear good. 15 percent opined results obtained by Ancuti's method as shown in column (e) of Figure 4 to be better. 15 percent opined results obtained by Ancuti's method as shown in column (f) of Figure 4 to be better. 50 percent of the samples opined results obtained by proposed method are better as shown in column (g) of Figure 4.



(a) (b) (c) (d) (e)

Fig. 4. Comparison of results of proposed framework with different state of art techniques (a) Input underwater image, (b) UDCP 2013 [9], (c) ANCUTI 2014 [1], (d) ANCUTI 2016 [2], (e) ANCUTI 2017 [5], (f) ANCUTI 2018 [4], (g) Proposed framework.

We compare the results of the color palettes of state of art techniques available with the proposed approach. We find that the colors are right and clearly distinguishable. Figure 5 shows the comparison.

(a) (b) (c) (d) (e) (f)

Fig. 5. Comparison of color palettes of results of proposed framework with different state of art techniques (a) UDCP 2013 [9], (b) ANCUTI 2014 [1], (c) ANCUTI 2016 [2], (d) ANCUTI 2017 [5], (e) ANCUTI 2018 [4], (f) Proposed framework.

4. Conclusions

In this paper, we have proposed a framework for enhancement of underwater images. Towards this, we have performed enhancement of underwater images using color balance and fusion using Laplacian and Gaussian pyramid. We have fused images obtained after color balancing and edge sharpening to generate enhanced underwater image. The performance of the proposed framework is demonstrated using qualitative evaluation. We show, the results obtained through the proposed fusion framework outperforms the state of art enhancement methods qualitatively. The proposed approach can also be used for enhancement of other kind of images like foggy or hazy on ground images.

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