Underwater Image Enhancement by Dark Channel Prior

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Abstract— **Light scattering and color change are two main problems in underwater images. Due to light scattering, incident light gets reflected and deflected multiple times by particles present in the water. This degrades the visibility and contrast of the underwater image. Dark channel prior is method used for removing the haze present in the underwater image. It is based on a key observation - most local patches in haze-free underwater images contain some pixels which have very low intensities in at least one color channel. Using this prior with the haze imaging color model estimates the thickness of the haze and recover a high quality haze-free image. This method does not require images with different exposure values, and is entirely based on the attenuation experienced by point across multiple frames. In this paper underwater image enhancement using Dark channel Prior is attempted. Results shows that the performance of this method is better compared to image enhancement using histogram equalization**

Keywords— ***Local patches, Dark channel prior, MATLAB/Simulink***

I. INTRODUCTION

Image enhancement improves the visibility of one aspect or component of an image. It refers to sharpening of image features such as boundaries, or contrast to make a graphic display. This is mainly useful for display & analysis. This process will not increase the intrinsic information of an image. This includes gray level & contrast manipulation, noise reduction, sharpening, filtering, interpolation and magnification, pseudo coloring, and so on. Image enhancement uses qualitative subjective approach to produce a more visually pleasing image [1], [2].

Acquiring clear images in underwater environments is an important issue in ocean engineering. The quality of underwater images plays a pivotal role in scientific missions such as monitoring sea life, taking census of populations, and assessing geological or biological environments. Capturing images underwater is challenging, mostly due to haze caused by light that is reflected from a surface and is deflected and scattered by water particles. Due to varying degrees of attenuation encountered by different wavelengths of light, underwater images always dominated by a bluish tone . Light scattering and color change result in contrast loss and color deviation in images acquired underwater. For example Fig.1.

Haze is caused by suspended particles such as sand, minerals, and plankton that exist in lakes, oceans, and rivers. As light reflected from objects propagates toward the camera, a portion of the light meets these suspended particles. This in turn absorbs and scatters the light beam, as illustrated in Fig.1. In the absence of blackbody radiation, the multi-scattering process along the course of propagation further disperses the beam into homogeneous background light.

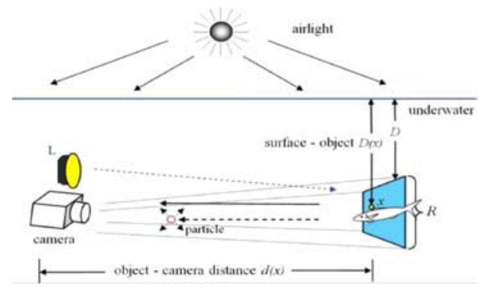


Figure 1. Natural light enters from air to an underwater scene point

Light scattering and color change can be corrected by contrast enhancement and image dehazing techniques. In this paper the performance of image enhancement using Dark channel prior is compared with that of Histogram equalization.

A. Histogram Equalization

Histogram equalization (HE) is popular method of contrast adjustment using the images histogram and also enhances a given image [3]. In this method, transformation

T is to be designed in such a way that the gray value in the output is equally distributed in [0, 1]. It is also called histogram flattening. Histogram equalization method in which histogram is modified by spreading the gray level areas. When an image's histogram is made equal, all pixel values of the image are redistributed so there are approximately an equal number of pixels to each of the user-specified output gray-scale classes e.g., 32, 64, and 256. Contrast is increased at the most populated range of brightness values of the histogram. For very bright or dark parts of the image, it automatically reduces the contrast associated with the ends of a normally distributed histogram. It can also divide pixels into different groups, if few output values are over a wide range. But this method is effective only when the original image has poor contrast to start with, otherwise it may degrade the image quality.

B. Image Dehazing

When one takes a picture in foggy weather conditions, the obtained image often suffers from poor visibility. The distant objects in the fog lose the contrasts and get blurred with their surroundings. This is because the reflected light from these objects, before it reaches the camera is attenuated in the air and further blended with the atmospheric light scattered by some aerosols (e.g., dust and water-droplets). Also for this reason, the colors of these objects gets faded and become much similar to the fog, the similarity of which depending on the distances of them to the camera.

The image dehazing is essentially an under-constrained problem. The general principle of solving such problems is therefore to explore additional priors or constraints. Following this idea, deriving an inherent boundary constraint on the scene transmission. This constraint combined with a weighted L_1-norm based contextual regularization between neighboring pixels, is formalized into an optimization problem to recover the unknown transmission. Dehazing method requires only a few general assumptions and can restore a haze-free image of high quality with faithful colors and fine edge details.

II. Dark Channel Prior

Dark channel prior method can produce a natural haze-free image. However, because this approach is based on a statistically independent assumption in a local patch, it requires the independent components varying significantly. Any lack of variation or low signal-to-noise ratio (e.g., in dense haze region) will make the statistics unreliable. Moreover, as the statistics is based on color information, it is invalid for grayscale images and difficult to handle dense haze which is often colorless and prone to noise [4]. Main contributions of dark channel method as follows: 1) The Separating an image into diffuse and specular components is an ill-posed problem due to lack of observations. 2) The observed color of an image is formed from the spectral energy distributions of the light reflected by the surface reflectance, and the intensity of the color is determined by the imaging geometry. 3) The dark channel is taken from the lowest intensity value among RGB channels at each pixel.

The DCP approach is able to handle distant objects even in the heavy haze image. It does not rely on significant variance on transmission or surface shading in the input image. The result contains few halo artifacts. Like any approach using a strong assumption, our approach also has its own limitation. The dark channel prior may be invalid when the scene object is inherently similar to the air light over a large local region and no shadow is cast on the object. The complete dehazing procedure is summarized in Algorithm 1 as shown in fig 2.

Algorithm 1: Underwater Image Haze and Noise Removal via Dark Channel Followed by Dehazing

1. Estimate I by Color models contrast variation in input image Y

2. Estimate transmission, t, and atmospheric light, a_∞ (e.g. dark channel prior) from I

3. Dehaze I through inversion of Eq. (1) to obtain the restored image: the scene radiance estimate R

A. Color Feature Extraction

A color image is a combination of some basic colors. In each individual pixel of a color image (termed 'true color') down into Red, Green and Blue values. We are going to get as a result, for the entire image is 3 matrices, each one representing color features. The three matrices are arranging in sequential order, next to each other creating a 3 dimensional m by n by 3 matrixes. 1) Three color planes namely Red, Green and Blue are separated.2) for each plane row mean and column mean of colors are calculated.3) The average of all row means and all columns means are calculated for each color plane.4) The features of all 3 planes are combined to form a feature vector. Once the feature vectors are generated for all images in the database, they are stored in a feature data set [5].

B. Estimating the Light Source of Illumination

The underwater image color constancy algorithms are based on simplifying assumptions such as restricted (limited number of image colors which can be observed under a specific illuminant), the distribution of colors that are present in an image (*e.g.* white patch) and the set of possible light sources. The dimensions should be Px3, where P is the number of data points and 3 is the number of color channels.

To estimate the color of the light source to compute the canonical range's for the light illumination type (i.e., pixels, Edges and Gradient). For accurate performance, the canonical range must be learned using images that are a representative set of real-world surfaces [6]. Also, all images that are used to learn the canonical range must be images that are illuminated by the same light source. To take illumination from all directions into account, let us consider an infinitesimal patch of the extended light source, of an image size.

The Color transmission algorithm is based on the average reflectance in a scene under a neutral light source is achromatic. In these two algorithms are proven to be important instantiations of the Minkowski-norm

$$L_c(P) = \left(f_c^p(x)dx\right)^{\frac{1}{p}} = ke_c$$

Where c = {R, G, B} and k is a multiplicative constant chosen such that the illuminant color, e = $(e_R, e_G, e_B)^T$, has unit length.

C. Dark Channel Estimation

The dark channel prior is based on the following observation on haze-free outdoor images: in most of the non-sky patches, at least one color channel has very low intensity at some pixels. In other words, the minimum intensity in such a patch should have a very low value. Formally, for an image *I*, we define

$$I^{dark}(x) = \min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(I^c(y)\right)\right) \qquad (1)$$

Where I_c is a color channel of *I* and Ω(x) is a local patch centered at *x*. Our observation says that except for the water color region, the intensity of *I* dark is low and tends to be zero, if *I* is a haze-free underwater image.

The low intensities in the dark channel are mainly due to three factors: a) shadows. e.g., the shadows of leaves, trees and rocks in landscape images;b) colorful objects or surfaces. e.g., any object (for example, green grass/tree/plant, red or yellow flower/leaf, and blue water surface) lacking color in any color channel will result in low values in the dark channel; c) dark objects or surfaces. e.g.,dark tree trunk and stone. As the natural outdoor images are usually full of shadows and colorful, the dark channels of these images are dark [7], [8].

D. Haze Removal

The dark channel prior relies on sample minima; it is especially sensitive to outliers [9]. Various approaches can be taken to robustly estimate the dark channel, and by extension the transmission map, considering the presence of noise. The hazy image prior to performing the dehazing process is a natural approach to handling the problem of noise in underwater scene radiance recovery [10].

In our restoration scheme, dehazing as a pre-processing step is especially convenient considering that it is already necessary for estimating the atmospheric light and transmission map. In the dehazing step, we can treat our image model as: Y = I + n, with the task being only to estimate I, which encapsulates the hazy image. After the hazy image is dehazed, the rest of the dehazing process is exactly the same as in the noise-free case.

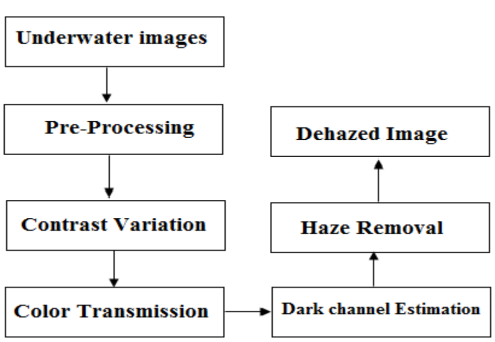


Figure 2. Flow Chart of Dehazing Process

III. Simulation Results

The performance of the dark channel algorithm is evaluated for underwater images. and videos downloaded from youtube. Results demonstrate haze removing of the dark channel prior algorithm over histogram equalization. Fig.3 and Fig.4 shows the result after processing with a dark channel prior algorithm and histogram equalization. Performance evaluation of both dark channel prior and histogram equalization is shown in Table 1.

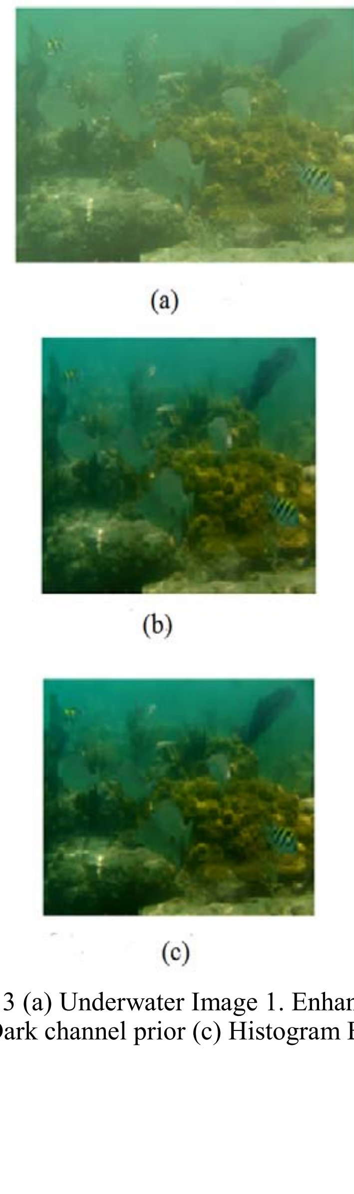
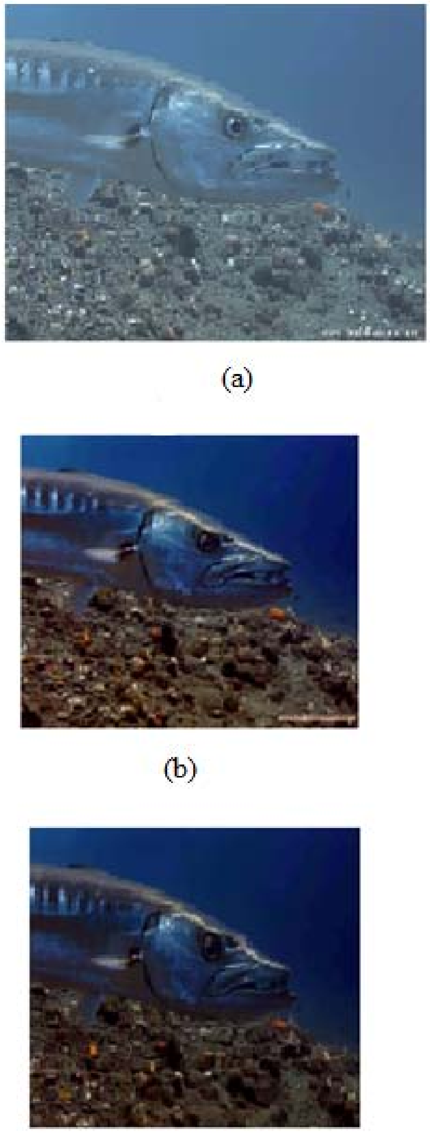


Figure 3 (a) Underwater Image 1. Enhanced Image using (b) Dark channel prior (c) Histogram Equalization



(a)

(b)

(c)

Figure 4 (a). Underwater Image2. Enhanced Image using (b) Dark channel prior (c) Histogram Equalization

	PSNR	
	Underwater image1	Underwater image2
Dark Channel Prior	50.4035dB	48.7065dB
Histogram Equalization	25.3084dB	22.2872dB

TABLE 1 QUANTITATIVE PERFORMANCE ANALYSIS

IV. CONCLUSION

The Dehazing algorithm effectively restore image color balance and remove haze over histogram equalization. Noexisting techniques can handle light scattering and color change distortions suffered by underwater images simultaneously. The experimental results demonstrate superior haze removing and color balancing capabilities of the DCP algorithm over traditional dehazing and color methods. However, the salinity and the amount of suspended particles in ocean water vary with time, location, and season, making accurate measurement of the rate of light energy loss is difficult. Errors in the rate of light energy loss will affect the precision of both the water depth and the underwater propagation distance. A very simple but powerful prior is called dark channel prior, for underwater image haze removal. The dark channel prior is based on the statistics of the underwater images. Applying the prior into the haze imaging model, haze can be effectively removed. Though, haze can be removed effectively in this paper, color change distortion still exist in the underwater image. Wavelength compensation of enhancement technique to be used for color change distortion in future.

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