MITIGATING THE EFFECT OF OPTICAL BACK-SCATTER IN MULTISPECTRAL UNDERWATER IMAGING

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ABSTRACT

Spectral information of an underwater scene, which can be found from a set of underwater multispectral images, is a very useful technique for extracting information from underwater world. But, underwater imaging is problematic even in multispectral image format. The main problem is the effect of optical back-scatter, which changes the scene reflectance value in each spectral band and this causes inaccuracy in the spectral information. In this work, a filter is used to detect the level of optical back-scatter in each spectral band from a set of multispectral images. Extraction of an underwater object spectra can be done by subtracting the estimated level of optical back-scatter and scaling the remainder in each spectral band from the captured image in the corresponding band. An experiment is designed to show the performance of the proposed filter for correcting the set of multispectral underwater images and recovering the pixel spectra. The multispectral images are captured in 33 bands in clear and different levels of turbid water. The results of processing experimental images in turbid water show that the effect of optical back-scatter can be mitigated in the image of each spectral band and as a result the spectra of the object can be recovered. However, for very high level of turbid water the recovery is limited because of the effect of extinction.

***Index Terms*—** Optical back-scatter, Underwater image, Multispectral image, Spectral reflectance

I. INTRODUCTION

Underwater imaging is widely used in different underwater applications [1] to extract information, such as marine biology [2], [3], [4], underwater target and mine detection [5], [6] and the inspection of underwater pipelines and structures [7], [8]. Multispectral imaging [9] provides additional information over RGB images [10], because multispectral imaging provides an estimate for the scene reflectance spectrum at each image pixel by measuring intensities at several spectral bands. Accurate estimation spectral reflectance helps better surveying and understanding of underwater life [11], [2], [4]. However, detecting accurate spectral features of a scene from an underwater multispectral image is problematic.

One of the main problems in underwater imaging is optical back-scatter, which is light scattered by suspended particles towards the camera. Optical back-scatter adds to the pixel intensity and as a result causes a change in the measured pixel reflectance spectrum. The magnitude of this extra component depends on different parameters, such as wavelength, the density and size of suspended particles in water and also the length of optical path. Therefore, the recorded reflectance spectrum of an underwater scene is not reliable. The effect of optical backscatter has been studied in underwater multispectral imaging [12], [13], but no general solution is given.

Previous studies have shown it is possible to compensate for the effect of optical back-scatter [14], [15], [16], but these studies are concerned with recovery of pixel intensity in RGB images. This work focuses on mitigating the effect of optical back-scatter in multispectral images. The aim is to recover reflectance spectrum for each pixel.

This paper is organised as follows. Firstly, a simple model of a degraded image pixel in turbid water in visible wavelengths is explained. Also, the recovery of the pixel intensity and then calculation of the pixel reflectance are explained. A method of estimating optical back-scatter for a degraded image pixel is described. A water tank experiment is used to provide a controlled imaging situation for which a clear reference spectrum is available. The experimental procedure and the results are presented in Sections IV and V, and finally the conclusion is given in Section VI.

II. IMAGE MODEL IN TURBID WATER

II-A. Simple Image Model

A model of an image pixel in a specific wavelength (λ) and in a turbid medium, $I_\lambda(x,y)$, is represented by Equation (1) [18]. This is known as additive model in literature [14].

$$I_\lambda(x,y) = b_\lambda(x,y) + a_\lambda(x,y)F_\lambda(x,y), \qquad (1)$$

where $b_\lambda(x,y)$ is the optical back-scatter, $a_\lambda(x,y)$ is the attenuation factor (representing optical extinction) and

$F_\lambda(x,y)$, the scene intensity in clear condition at a specific wavelength and spatial pixel position.

Recovery of the intensity of a pixel, $\hat{I}_\lambda(x,y)$, can be achieved by rearranging Equation (1).

$$\hat{I}_\lambda(x,y) = \frac{I_\lambda(x,y) - b_\lambda(x,y)}{a_\lambda(x,y)}. \tag{2}$$

II-B. Spectral Reflectance Recovery

Unlike pixel intensity, surface spectral reflectance is an inherent property of an object and is independent of other parameters like time, location and illumination. Spectral reflectance can not be measured directly and instead must be calculated. The conversion of pixel intensity to reflectance can be done by scaling the pixel intensity spectrum by the spectral radiance of a white reference [19]. Therefore, by scaling the intensity spectrum of the recovered pixel with a white reference spectrum the recovered spectral reflectance of an image pixel can be obtained.

III. METHOD

The proposed method is based on Equation (2), by which the contrast loss can be mitigated by subtracting optical back-scatter, $b_\lambda(x,y)$, from the degraded underwater image and then multiplying the image by a scaling parameter, $\frac{1}{a_\lambda(x,y)}$. The key issue is how to estimate $b_\lambda(x,y)$. Oakley and Bu [14] present a new statistical method, based on minimisation of a cost function, to estimate the level of optical backscatter, without the need for information on the physical properties of the scene. However, in their work the optical back-scatter is assumed constant in the image. This assumption is not valid for underwater images since the optical back-scatter varies spatially [15].

In [20], the algorithm of Oakley-Bu Cost Function is extended to a variable spatial distribution of optical back-scatter. It is shown mathematically in [20] that the extended cost function has a minimum value at γ. Therefore, the value of γ can be estimated by Equation (3).

$$\begin{aligned} S_\lambda(\gamma) = \frac{1}{P}\sum_{p=1}^{P}\left(\frac{I_\lambda(p) - \bar{I}_\lambda^{cf}(p)}{\bar{I}_\lambda^{cf}(p) - \gamma \bar{I}_\lambda(p)}\right)^2 \\ .\exp\left(\frac{1}{P}\sum_{p=1}^{P}\ln(\bar{I}_\lambda^{cf}(p) - \gamma \bar{I}_\lambda(p))^2\right), \end{aligned} \tag{3}$$

where p represents each image pixel in spatial position of (x,y), P is the total number of pixels, λ is the specific wavelength, I_λ is the degraded image, $\bar{I}_\lambda^{cf}$ is the smooth version of the image, which is calculated by recursive Guassian filter with σ_{cf} filter parameter, and $\bar{I_\lambda}$ is the smooth version of the image, which is calculated by recursive Guassian filter with σ_B filter parameter. The scaling of image, $\frac{1}{a_\lambda(x,y)}$, to recover for the effect of extinction can be done by stretching the image histogram, after the degraded image is compensated for the effect of optical back-scatter.

IV. EXPERIMENTAL PROCEDURE

A water tank experiment is designed to provide an imaging system in a controlled environment, that captures underwater multispectral images from different scene contents in both turbid and clear water conditions. The clear water condition is used to obtain the pixel reflectance spectrum in a non scattering condition (no optical back-scatter). The level of optical back-scatter in turbid water is kept constant during imaging by keeping the wavelength, particle size and density and length of the optical path constant. A water tank is used to represent underwater medium. A translation stage is designed to translate the camera and light source forward and backward, while the multispectral camera and light source are both set in a specific angle and height relative to the water tank. These conditions are thus similar to those in underwater imaging with an ROV. Figure 1 shows the arrangement of the water tank experiment.

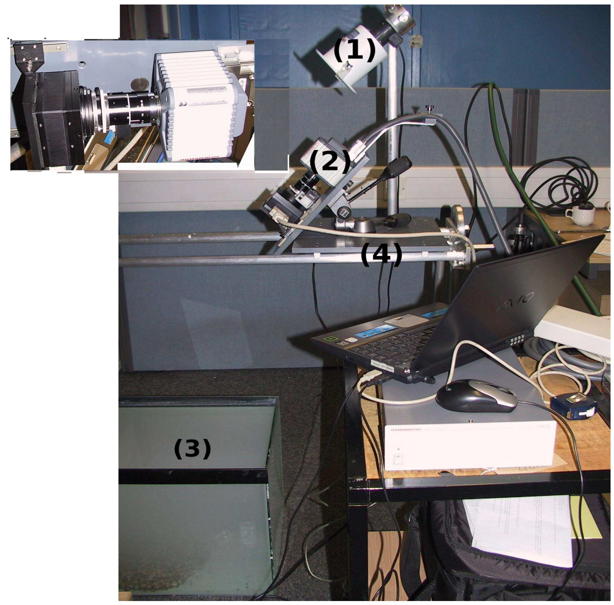

Fig. 1. Water tank experimental setup. 1)Light source 2)Multispectral camera 3)Water tank 4)Translation stage.

The tank is filled with tap water and, to represent turbid water, particles in a representative size range are added to the tap water. Emulsion paint, which is mainly composed of Titanium Dioxide (TiO_2), is used to represent scattering particles. The particles have a diameter in the range 0.2 to $2.5\mu m$ [21], which is similar to some types of problematic mineral particles in underwater imaging [22]. The particles of emulsion paint settle very slowly at the bottom of water tank, providing a constant level of scattering for a limited time. Therefore, the number of sample images should be chosen in such a way that the total capturing time be less than the settling time of particles.

Three series of continuous images, each contains 10 sample images, are captured by Hamamatsu ORCA-ER camera at different scenes from clear, T_0, and turbid water conditions, T_1 and T_2, at 20^o water temperature, in $10nm$ bandwidth of visible range at $440nm$ - $720nm$ central wavelengths. The images from turbid water are captured at the same camera positions that clear images were captured. Water turbidity at T_1 and T_2 are made by adding $0.3gr/100Liters$ and $0.7gr/100Liters$ of emulsion paint to tap water respectively. The optical distance is $122.08cm$ considering the water refractive index as 1.3334 at water temperature of 20^o [23] and [24]. The multispectral camera is set with angle of $\beta1 = 42^o$. The spatial distance between two camera locations for capturing two adjacent images is $4mm$. The camera aperture and focus are set to 4.0 and 1.15 respectively. A halogen lamp is used as the light source and is fixed with angle of $\beta2 = 45^o$. The experiment is done in a dark room with no other source of illumination except the halogen lamp. Water plants, sea shells and gravels are used as scene contents.

A dark multispectral images are captured, when the camera is covered completely by a black cloth, at $440nm$ - $720nm$ central wavelengths with $10nm$ bandwidth. The multispectral images are corrected by subtracting the value of dark multispectral images for the effect of camera dark current noise and fixed pattern noise at respective wavelengths [9]. The radiance of a white object in clear water is measured with telespectro-radiometer as a reference for the illumination spectrum in clear water. This is used to calculate the reflectance value.

V. RESULTS

Optical back-scatter is estimated for 10 degraded images in clear (T_0), medium (T_1) and high (T_2) levels of water turbidity at wavelengths of $420nm$ to $720nm$ by the proposed algorithm. The parameters are set to $\sigma_{cf} = 4$ and $\sigma_B = 180$. The estimated values of optical back-scatter are used to recover the degraded image pixels at different wavelengths. The scaling for the recovered image is done by stretching the image histogram.

First, the accuracy of the proposed algorithm for optical back-scatter estimation is experimentally investigated. There is always some level of optical back-scatter even for images in clear water condition. Therefore, it is expected that when the proposed algorithm is applied to a clear underwater image, it detects this low level of optical back-scatter. Also, when the level of water turbidity is higher, a higher level of back-scatter is expected. Figure 2 presents the plot of estimated γ for different levels of water turbidity, T_0, T_1 and T_2, and for 10 images at wavelength of $600nm$. It can be seen from the plot that the value of estimated γ is different for each level and is associated with the level of water turbidity.

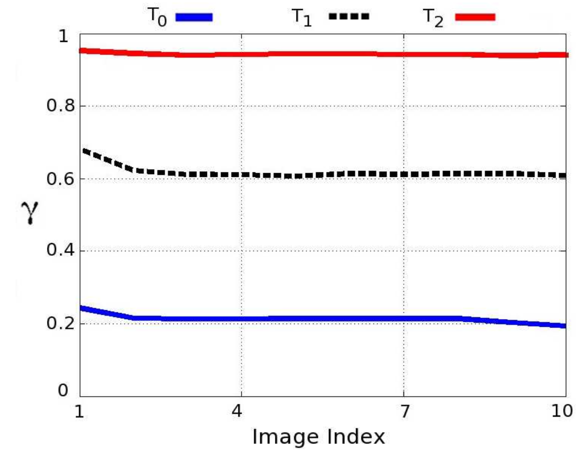

Fig. 2. The plot of γ versus image index, for three water turbidity levels, T_0, T_1 and T_2 at wavelength of $600nm$.

Next, the consistency of the proposed algorithm for optical back-scatter estimation is investigated. For a series of continuous images, when the level of water turbidity, the optical depth, the illumination and the wavelength remain unchanged, it is expected that the value of optical back-scatter remains unchanged over continuous images. The position of the light source and the water turbidity are kept constant during the capture of 10 test images. As a result, the level of optical back-scatter at each narrow spectral band is expected to be consistent over the 10 test images. Since the position of light source is consistent, the shape of $\bar{I}$ is similar for all of the images. Hence, to have a constant level of optical back-scatter, the value of estimated γ should be consistent over continuous images.

The value of estimated γ is plotted versus image index at each wavelength and presented in Figure 3. It can be seen that the value of γ is consistent within 10 test images at each spectral band. However, the estimated γ at image 1 is slightly higher ($< 10\%$ difference with respect to the γ value at image 2 - image 10). This can be because when image 1 was captured the particles have not been settled properly in water tank, where as at the time of imaging for image 2 and after, the particles were settled and provided a constant level of optical scattering.

The estimated values of optical back-scatter are used to recover the degraded image pixels at different levels of water turbidity. A selection of improved images is presented in Figure 4. It can be seen that the improved images from T_0 and T_1 (Figures 4(a) and (b) at column (ii)) are similar. The improved images show the scene content without any scattering effect. This confirms that the algorithm can detect the level of optical back-scatter and correct the image appropriately.

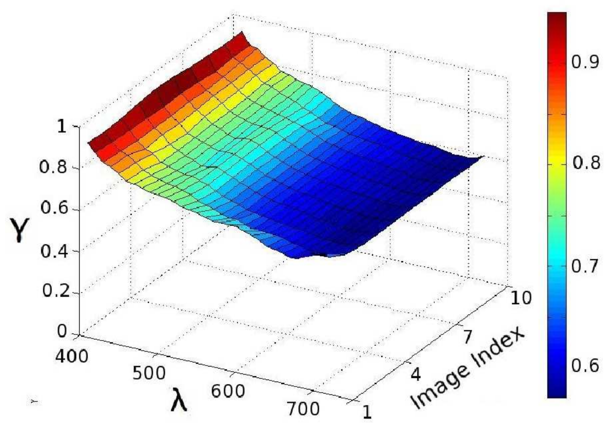

Fig. 3. The surf plot of γ versus image index at different spectral bands.

VI. CONCLUSION

The main problem in underwater imaging is the effect of optical back-scatter, which causes a change in the pixel value and as a result inaccuracy in the pixel spectral information. The experimental results show that the proposed method can estimate the accurate level of optical back-scatter and compensate for it at different spectral bands in visible wavelengths and for different levels of water turbidity. Therefore, the original pixel value can be recovered from the degraded pixel and as a result the pixel spectral information of an underwater scene can be found. The advantage of the proposed method is that it compensates the effect of optical back-scatter with no information of the physical properties of the medium.

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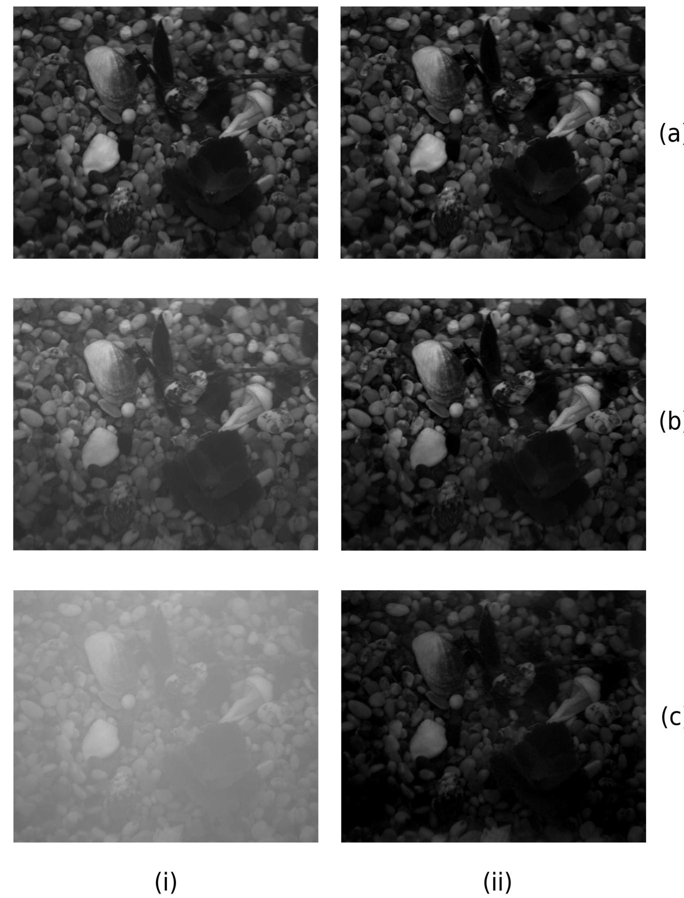

Fig. 4. The selection of i) original images, and ii) improved images at 600 nm for different levels of water turbidity, a) T_0, b) T_1 and c) T_2.

VII. REFERENCES

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