A Novel Adaptive Restoration for Underwater Image Quality Degradation

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Abstract--- In this paper, we present one simplify underwater image restoration model combined with Total variation (TV) regularized Richardson-Lucy (RL) algorithm. Poor visibility in the sea and the variations in the illumination, viewpoints, etc., have been comprehensively taken into consideration for image restoration. An adaptive image restoration strategy by Improvement signal-to-noise ratio (ISNR) is then made full use of to undertake the underwater image restoration. A non-reference restored image quality evaluation criterion called relative gray mean grads (RGMG) is defined on the basis of other evaluation criterion called gray mean grads (GMG). It is shown in the simulation experiment that the proposed approach could achieve great performances in both robustness and effectiveness, with good behaviors in the vision effects and matching precision for the underwater images.

Keywords---Underwater image restoration; total variation(TV); relative gray mean grads(RGMG); Richardson-Lucy (RL) algorithm; Improvement signal-to-noise ratio (ISNR);

I. INTRODUCTION

Image deblurring/restoration is a classical linear inverse problem. The challenge in most inverse problems (linear or not) is that they are ill-posed. To cope with the ill-posed nature of these problems, a large number of techniques have been proposed, most of them under the regularization or the Bayesian frameworks [1]. These techniques are supported on some form of a priori knowledge about the original image to be estimated. Some of these methods, including wavelet-based priors/regularizers [1, 2, 3, 4], Markov random field priors [14, 15] and total variation regularization [5, 6, 7] are considered the state-of-the-art.

Recently, the range of application of Total variation (TV)-based methods has been successfully extended to the imaging problems, such as inpainting, non-blind and blind deconvolution, and processing of vector-valued images [7]. Arguably, the successes of TV-based regularization lies on a good balance between the ability to model piecewise smooth images and the difficulty of the resulting optimization problems. In fact, the TV regularizer is convex and has stimulated a good amount of research on efficient algorithms for computing optimal or nearly optimal solutions [6, 7, 8, 9]. However, the 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. Hou et al. [10, 11, 12] incorporated the underwater optical properties to the traditional image restoration approach. Trucco and Olmos [13] presented a self-tuning restoration filter based on a simplified version of the Jaffe-McGlamery image formation model. Model complexity and uncertainty on parameter values are probably two important reasons discouraging the inclusion of image formation models in image processing algorithms.

In this paper, we propose the design of an image adaptive restoration method tackling the underwater image quality degradation. The structure of the paper is as follows. Section II describes the basic framework of our approach. Section III underwater imaging theory is presented; Section IV the proposed method is discussed. Section V lists our experimental results and analysis, and Section VI comes to the conclusions.

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II. GENERAL FRAMEWORK

A brief flow chart of the underwater image adaptive restoration is shown in Fig.1, which is made up of several steps, including the underwater image acquisition, model parameter initialization, and adaptive Image restoration. We simplify the description of the underwater imaging model and then we combine the RL algorithm with a regularization constraint based on the total variation (TV). After this, we develop an adaptive image restoration strategy by Improvement signal-to-noise ratio (ISNR).

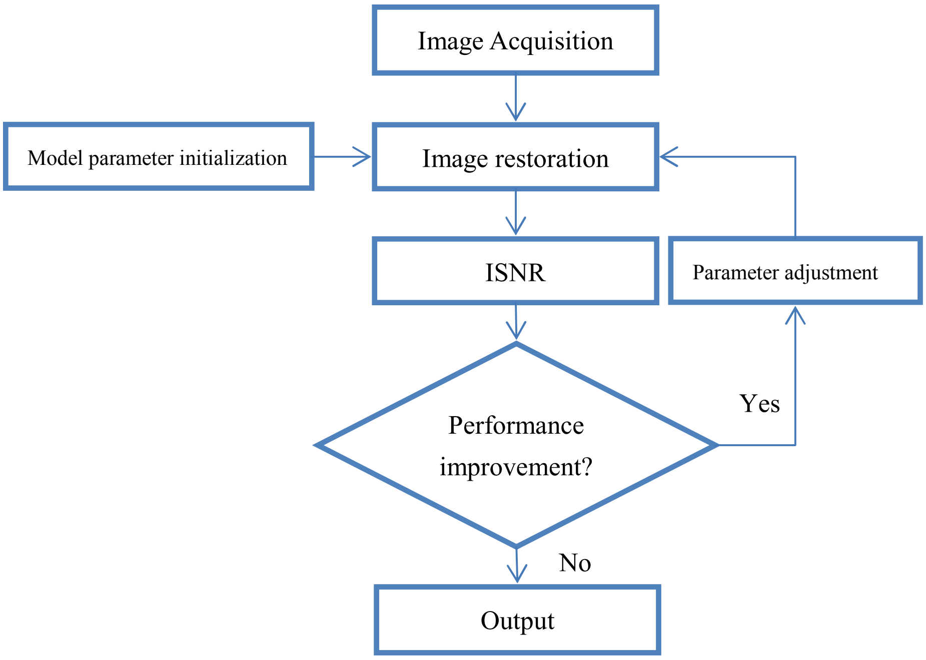


Fig.1 the flow chart of the underwater image restoration

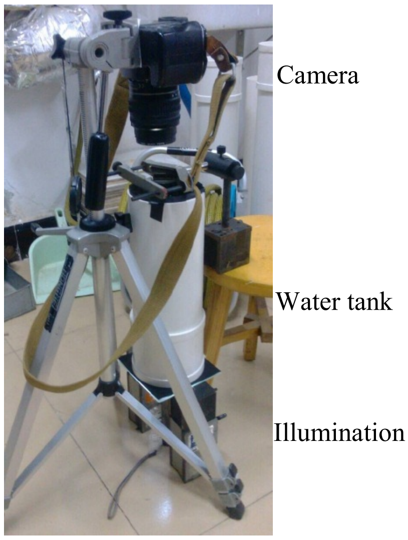


Fig.2 The underwater imaging system

III. UNDERWATER IMAGES

A. The Jaffe-McGlamery Model

In this paper, the Jaffe-McGlamery underwater image formation model [18, 19] has been first taken to explain the inherent and apparent properties of the light propagation in the water, including the direct component E_d, the forward-scattered component E_f and the backscatter component E_b .Therefore, the total irradiance E_T reads:

$$E_T = E_d + E_f + E_b \tag{1}$$

The forward-scattered component can then be calculated from the direct component via the convolution relationship,

$$E_f(x,y) = E_d(x,y) * g(x,y,R_c,G,c,B) \tag{2}$$

$$g = \{\exp(-GR_c) - \exp(-cR_c)\}\, F^{-1}\exp(-BR_c f) \tag{3}$$

Where G is an empirical Constant (G <<C), B is an empirical damping factor, and F^{-1}, which is a radial frequency in cycles/rd. R_c is the distance from $(x\ ,y\ )$ position on the reflectance map to the camera.

B. Simplified Degraded Model

Here one simplification for the underwater image degradation model is considered by the difference of exponentials in the forward scatter model as an experimental constant K,

$$K \approx [\exp(-GR_c) - \exp(-cR_c)] \tag{4}$$

Trucco and Olmos'l assumptions [13] point to low-backscatter, shallow-water conditions as the optimal environment for technique. The Fourier transform of the resulting, simplified imaging model is simply

$$G(f, R_c, c, K) \approx K\exp(-cR_c w) \tag{5}$$

In underwater environment, deflections can be due to particles or to particulate matter with refraction index different from that of the water. Like the complex optical refraction caused by atmospheric turbulence. According to the Lambert-Beer empirical law [16, 17], the decays of light intensity in the two mediums are all related to the properties of the material. Underwater degraded images are of same visual effects as images taken with serious atmospheric interference. Hufnagel and Stanley [20] proposed an image degradation model based on atmospheric turbulence physical property,

$$H(u,v) = \exp[-k(u^2+v^2)^{\frac{5}{6}}] \tag{6}$$

A Simplified degradation model,

$$H(u,v) = K\exp[-\alpha(u^2+v^2)^{\beta}] \tag{7}$$

β is the corresponding parameter of atmospheric turbulence, α is the parameter of environmental condition.

IV. IMAGE RESTORATION

C. Total variation (TV) regularized RL algorithm

In linear image restoration problems, the goal is to estimate an original image $f(x,y)$ from an observed blured and noisy version $g(x,y)$,

$$g(x,y) = H[f(x,y)] + n(x,y) \tag{8}$$

where $f(x,y)$ is the original image, H is a linear operator representing, for example, the blur point spread function (PSF), and $n(x,y)$ is a sample of a zero-mean white Gaussian field of variance σ^2.

Total variation (TV) regularized RL algorithm iterative formula:

$$f_{i+1}(x,y) = [\frac{g(x,y)}{f_i(x,y)\otimes h(x,y)}h(x,y)] \times \frac{f_i(x,y)}{1-\lambda Div(\frac{\nabla f_i(x,y)}{|\nabla f_i(x,y)|})} \tag{9}$$

where ∇ is gradient operation, λ is regularization parameter and Div is divergence. We propose the Total variation (TV) regularized RL algorithm to suppresses the unstable oscillations while preserving the underwater image edges.

D. Model Parameter Estimation

We use the average gradient to evaluate the performance of the restored underwater image. That is:

$$GMG(f) = \frac{1}{(M-1)(N-1)}\sum_{x=1}^{M-1}\sum_{y=1}^{N-1}\sqrt{\frac{(f_x')^2+(f_y')^2}{2}} \tag{10}$$

f_x' and f_y' represent direction gradient.

$$RGMG = \frac{GMG(\hat{f}) - GMG(g)}{GMG(g)} \tag{11}$$

where $\hat{f}$ is the restoration image, g is the degraded image.

V. SIMULATION EXPERIMENT

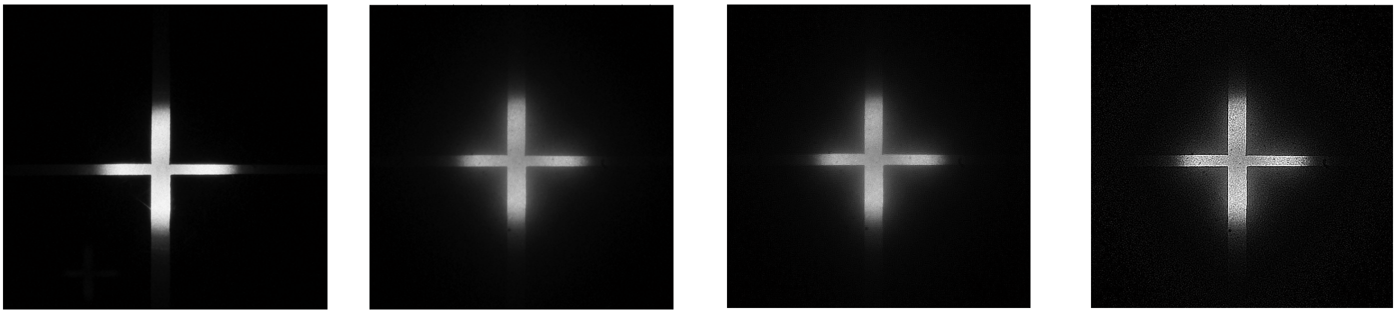
In our simulations experiments, we first set up an underwater imaging simulation system and the underwater optical images were collected with various depth of the water. Fig.2 is our developed underwater imaging system, including the illumination source used LED light source, the CCD camera, the illuminating surface and the sealed water tank. All the simulation experiments have been run on Windows 7 with at least 8 GB of memory and 2+GHz processor. The execution environment is under MATLAB 7.0. We set the stopping criteria as SNR improvements (ISNR) consecutive falling below the threshold. Table 1 show SNR improvements (ISNR) of the proposed approach,

$$ISNR = \| g(x,y) - f(x,y)\|^2 / \| \hat{f}(x,y) - f(x,y)\|^2$$

Fig.3 lists the no water image and the 5cm degraded underwater image and the restoration performance for one example underwater image taken in 5cm deep water. The proposed approach maintains the best brightness loss overall and minimizing the effect of the noise.

Outer iteration \ Inner iteration / ISNR (dB)	1	2	3	4	5
1	-0.114775	-0.0337464	-0.0268575	-0.0253282	-0.0248995
2	-0.0117345	-0.00341284	0.000143037	0.00185185	0.00185978
3	0.00186475	0.00186839	0.00187193	0.00187516	0.00187716

Table 1 ISNR of the proposed algorithm.

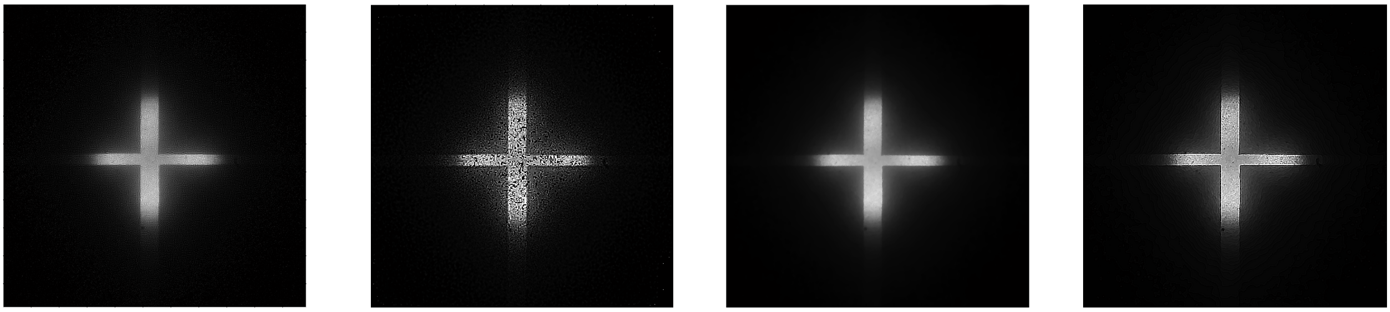


(a)No water image

(b) 5cm degraded image

(c) Direct Wiener filter (RGMG=353.95%)

(d) Wiener filter by proposed model (RGMG=427.21%)



(e) Direct RL (RGMG=233.80%)

(f) RL by proposed model (RGMG=316.52%)

(g) RLTV (RGMG=289.73%)

(h) RLTV by proposed model (RGMG=500.52%)

Fig.3 the original image and the degraded image and the restoration of the underwater image taken in 5cm deep water

VI. CONCLUSIONS

In this paper, we have focused on the adaptive restoration for underwater image quality degradation. We simplify the description of the underwater imaging model and then combine the RLTV algorithm and develop an adaptive image restoration strategy by ISNR, which will be computed to estimate the optimal model parameters. Simulation experiment shows that the proposed approach achieves a great performance in terms of RGMG. These results allow concluding that the proposed approach handles satisfactorily the problem of underwater image quality degradation.

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