Underwater Image Restoration by Turbulence Model based on Image Quality Evaluation

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Abstract

For the underwater degenerative image caused by obscure and noise, atmospheric turbulence model is utilized to construct the restoration model. By computing the underwater image quality function which is used to estimate the adaptive degradation model parameter, underwater image is restored through Wiener filters. The connection between image contrast and average gradients and model parameter is analyzed as well. The experiments show that the proposed method exerts powerful effort on restoration of the obscure underwater image caused by scattering. The proposed method has a better improvement on contrast and definition of underwater image than other common preprocessing methods and is especially suitable for further degradation model analysis and objective detection.

Keywords: Underwater Image; Image Restoration; Degradation Function; Turbulence Model; Image Quality Evaluation

1. Introduction

The image information processing ability is one of the most important for underwater vehicles to perform various missions. However, the underwater grayscale images often suffer of one or more of the following problems: limited range visibility, low contrast, non uniform lighting, blurring, bright artifacts, and noise [1,2]. Therefore, application of standard computer vision techniques to underwater imaging requires dealing first with these added problems. In addition, because of the complexity of underwater target and the variety condition of the sea, it’s difficult to make explanations overall and systematically for the imaging mechanism, also to obtain information of underwater environment and objects. Until now, there hasn’t been a system research on underwater image restoration.

When specialized hardware such as lasers, range gated light systems or polarized cameras is not available, image quality must be improved via software processing. On the image restoration aspect, Trucco and Olmos [3] presented a self-tuning restoration filter based on a simplified version of the Jaffe-McGlamery [4] image formation model. Two assumptions are made in order to design the restoration filter. The first one assumes uniform illumination (direct sunlight in shallow waters) and the second one is to consider only the forward component of the image model as the major degradation source, ignoring back scattering and the direct component. Optimal values of these parameters were estimated automatically for each individual image by optimizing a quality criterion based on a global contrast measure. Therefore, low backscatter and shallow-water conditions represent the optimal environment for this technique. Liu et al. [5] measured the PSF and MTF of seawater in the laboratory by means of the image transmission theory and used Wiener filters to restore the blurred underwater images. Grosso [6] and Voss [7] also measured the point spread function (PSF), precision is high, but the instruments are complicated and expensive, which is hardly to meet such needs as real-time processing. Yu et al. [8] proposed a laboratory facility to measure and calculate the PSF and the optic transfer function (OTF) of seawater. These deconvolution algorithms mentioned above are rigorous but hard to perform in a real situation because the parameters of the model are unknown. First of all, the attenuation and diffusion coefficients that characterize the water turbidity are only scarcely

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known in tables and can be extremely variable. Next, the most crucial parameter to recover is the depth of a given object point in the scene, which is necessary to correctly estimate the distance traveled by the light. Therefore, to the best of our knowledge, existing underwater restoration models are all proposed for some special underwater environments, which is not always applicable wildly.

Besides that, most widespread technology for underwater images are typical image enhancement approaches, such as histogram modification \cite{9}, homomorphic filtering, wavelet denoising, gradient transfer \cite{10} and some adaptive smoothing methods \cite{11}-\cite{13}. Part of them caused over-smoothing and detail missed which can be a nightmare for navigation and object recognition. In addition, the traditional algorithms are not adaptive and likely to be affected by noise and non uniform lighting. Zhang et al. \cite{14} proposed an underwater image processing approach based on atmospheric turbulence model. They test different model parameters to compare the restoration effect. Although they enhanced underwater image, this is not adaptive and without considering the relationship between the objective image quality and model parameters.

We try to address the low contrast, blurring present in underwater images by using a combination of turbulence model and underwater image quality estimation function. Optimal values of model parameter were estimated automatically for each individual image by optimizing a quality criterion based on a contrast measure and average gradient measure. The comparison results show that the proposed new method redresses the low contrast, compensate the attenuation and is especially suitable for unknown dark underwater environment restoration. Meanwhile, we described the connection between degraded images and the model parameter. This may be a basis for deep analysis.

This paper is organized as followed. In Section 2, underwater restoration theory is presented; in Section 3, underwater degradation model is briefly described; in Sections 4 the proposed method is discussed. Experimental results on real images are reported in Section 5.

2. Underwater degraded image

A major difficulty to process underwater images comes from light attenuation. Light attenuation limits the visibility distance, at about twenty meters in clear water and five meters or less in turbid water. The light attenuation process is caused by the absorption and scattering (see Fig.1). Absorption and scattering effects are due to the water itself and to other components such as dissolved organic matter or small observable floating particles. Absorption is the loss of power as light travels in the medium and it depends on the index of refraction of the medium. Scattering refers to any deflection from a straight-line propagation path. Forward scattering (randomly deviated light on its way from an object to the camera) generally leads to blurring of the image features. On the other hand, backward scattering (the fraction of the light reflected by the water towards the camera before it actually reaches the objects in the scene) generally limits the contrast of the images, generating a characteristic veil that superimposes itself on the image and hides the scene. In orders of magnitude, backscattering and marine snow are the greatest degradation factors, forward scattering comes second and attenuation follows closely \cite{1}.

A possible approach to deal with underwater images is to consider the image transmission in water as a linear system. Image restoration aims at recovering the original image \( f(x, y) \) from the observed image \( g(x, y) \) using (if available) explicit knowledge about the degradation function \( h(x, y) \) (also called point spread function PSF) and the noise characteristics \( n(x, y) \):

\[
g(x, y) = f(x, y) * h(x, y) + n(x, y)
\]

Where \( * \) denotes convolution. The degradation function \( h(x, y) \) includes the system response from the imaging system itself and the effects of the medium (water in our case). In the frequency domain, we have:

\[
G(u, v) = F(u, v)H(u, v) + N(u, v)
\]
3. Atmospheric turbulence model

Degradation model is a key to image restoration problem. 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, the decays of light intensity in the two mediums are all related to the properties of the material. The floating particles or the air mass not only absorb photons but also deviate incident rays of light. Photos taken from a far distance in the air also encounter the same problems as in water, that is, they are low contrast and optical blurry. Therefore, underwater degraded images are of same visual effect as images taken with serious atmospheric interference.

In 1964, Hufnagel and Stanley \cite{15} proposed an image degradation model based on atmospheric turbulence physical property, where,

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

(3)

\( k \) is turbulence constant, when \( k > 0.0025 \), it is termed as excessively turbulent, moderate turbulence when \( k \) is around 0.001, and slight turbulence if \( k < 0.00025 \) \cite{16,17}. Here, we adapt Formula 3 as the underwater degradation model, then we estimation \( k \) automatically

4. Model parameter estimation

4.1 Quality Assessment

Image quality has been an interesting and important research subject in digital image processing. The objective image quality metrics are classified in three groups: full reference (there exists an original image with which the distorted image is to be compared), no-reference or “blind” quality assessment and reduced-reference quality assessment (the reference image is only partially available, in the form of a set of extracted features). In the present case of underwater image processing, no original image is available to be compared, and therefore, no-reference metrics are necessary. The common approaches in determining the quality include the use of peak signal-to-noise ratio (PSNR) and the mean square errors (MSE). For the type of images we are interested in, a no-reference, or blind, objective image quality metric is needed,
in order to achieve these goals: 1) to define faithfully the quality of an image without a priori knowledge in different environments (e.g., different water optical properties); 2) independent of the content of an image; 3) immune or less sensitive to noises, especially those caused by the multiple scattering in underwater environments \(^{18}\). The establishment of such metrics is a critical component in the automated image restoration, where the computer system needs to know “when” to stop, and determine if it has found the best result, and if the “best” result is acceptable in a comparable underwater environment.

From the psychological research perspective of human visual perception for texture, Tamura et al. presented six elements of texture characteristics \(^{19}\). Among them, Contrast is closely related to the sharpness or resolution of an image, and usually defined by the differences between lighter and darker areas then divided by the combined brightness:

\[
F_{\text{con}} = \frac{S}{(S_1)^n} 
\]

\[
S_4 = \frac{M}{S^4} 
\]

Where, \(\mu_4\) is the fourth central moment and \(\sigma_2\) is variance. \(F_{\text{con}}\) is the whole image area contrast measurement.

Another objective image quality metric, we use the average gradient to evaluate the performance of the restored image. That is:

\[
AG = \frac{1}{(M-1)^2(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \left[ \frac{1}{2} \left( \frac{f_{i+1,j} - f_{i-1,j}}{\delta_x} \right)^2 + \left( \frac{f_{i,j+1} - f_{i,j-1}}{\delta_y} \right)^2 \right] 
\]

Where, \(f(i, j)\) is the pixel value of a \(M \times N\) restored image at position \((i, j)\). The average gradient reflects the clarity of the image. It can be used to measure the spatial resolution of the image, i.e., a larger average gradient means a higher spatial resolution \(^{20}\).

The key to automated processing is the ability to objectively determine underwater image quality, as small, incremental improvements caused by different model parameter in restored images cannot be measured by visual inspection due to time constraints and subjectivity. Therefore, a special, objective image quality metric (IQM) was developed here. That is Weighted Contrast Average Grads weighted (WCAG):

\[
WCAG_k = w_0 \left( 1 \frac{AG_0}{AG_k} \right) + w_1 \left( 1 \frac{F_{\text{con}0}}{F_{\text{con}}} \right) 
\]

Where, \(AG_0\) is the average gradient value of real image and \(AG_k\) is the average gradient value of restored image when the model parameter is \(k\). \(F_{\text{con}0}\) and \(F_{\text{con}}\) are contrasts of degraded image and restored image, respectively. Besides, \(w_0\) and \(w_1\) are weight coefficients, here \(w_0=0.8\) and \(w_1=0.2\).

### 4.2 Model parameter estimation

The restoration framework first determines the quality of the subject image by Formula (7), and arrives at a single value (WCAG\(k\)), which serves as a reference to future improvements. The optimization process starts with a slight turbulence model parameter, we consider the \(k\) is from 0.00025 to 0.0025, and apply the coarse-to-fine search strategy. The modeled degradation function is further used to deconvolve the real image to a restored version using Weiner filtering and its quality is then assessed by the same IQM. The resulting WCAG\(k\) is compared to the reference to determine if further optimization is needed. When no further improvements can be made, the optimization loop exits with restored images and derived model coefficient that may be important for estimate ocean optics further. Figure 2 is the flowchart of our project.
5. Experimental Results

This section summarizes two types of experiments: qualitative assessment of the restoration quality by visual inspection, and quantitative performance analysis using the proposed method.

5.1 Qualitative results

The images used in the framework testing were from internet. The water optical properties during the experiment were unknown. An attempt is made to evaluate the performance of other four enhancement algorithms used for underwater images. The images are processed using the tool Matlab. Figure 3 (a) expresses a group of blurring underwater images, the original underwater images are all low luminosity and restricted visibility. Figures 3(b) to (e) present various enhancement algorithms including: Density histogram adjustment (Fig.3 (b)), Histogram equalization enhancement (Fig. 3 (c)), Homomorphic filter enhancement results (Fig. 3 (d)) and Wavelet transform enhancement results (Fig. 3 (e)). These typical methods process with no a priori knowledge of the environment. They use qualitative subjective criteria to produce a more visually pleasing image and they do not rely on any physical model for the degradation formation. So, have produced mixed results for the various underwater environment. While the contrast of our proposed method is better, especially for underwater blurred image suffered bad backscatter as shown in Fig. 3(f).

5.2 Quantitative results

We assessed quantitatively the benefits of the restoration method for the images shown in Fig.3. Via the pathway shown in Table 1 and 2, comparisons of different approaches are carried out by calculating the image Contrast ($F_{con}$) & Average gradient (AG). Table 3 compares the WCAG with those methods proposed in above. The final results yield the best quantitative values, as well as the best estimation of model coefficient $k$.

Notice that the restored version of the fourth image in Fig.3(f) visually appears better than the restored image in Fig. 3(b)–(e) and larger WCAG value, although it have smaller contrast value than the Wavelet algorithm. This is a good example about the effective of our defined metric. The quality assessment results using quality function set up in our method are in accordance with visual inspection.
### Table 1. Image Contrast (F<sub>con</sub>) Comparisons

<table>
<thead>
<tr>
<th></th>
<th>F&lt;sub&gt;con&lt;/sub&gt;</th>
<th>Real images</th>
<th>Histogram adjustment</th>
<th>Histogram equalization</th>
<th>Wavelet transforms</th>
<th>Homomorphic filter</th>
<th>Our method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>39.2845</td>
<td>48.6645</td>
<td>64.4530</td>
<td>58.9594</td>
<td>45.5675</td>
<td>70.5687</td>
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<tr>
<td>Image 2</td>
<td>57.3444</td>
<td>70.6223</td>
<td>64.6460</td>
<td>60.3637</td>
<td>53.3556</td>
<td>91.1297</td>
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<tr>
<td>Image 3</td>
<td>57.3757</td>
<td>72.0121</td>
<td>64.6390</td>
<td>78.6182</td>
<td>48.0404</td>
<td>91.9372</td>
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<tr>
<td>Image 4</td>
<td>37.9757</td>
<td>44.1088</td>
<td>64.6151</td>
<td>66.3563</td>
<td>36.5721</td>
<td>61.6785</td>
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</table>

### Table 2. Average Gradient (AG) Comparisons

<table>
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<tr>
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<th>AG</th>
<th>Real images</th>
<th>Histogram adjustment</th>
<th>Histogram equalization</th>
<th>Wavelet transforms</th>
<th>Homomorphic filter</th>
<th>Our method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>1.8407</td>
<td>2.2685</td>
<td>2.7045</td>
<td>1.9850</td>
<td>2.3497</td>
<td>2.9984</td>
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<tr>
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<td>1.2665</td>
<td>1.5466</td>
<td>1.7452</td>
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<td>1.4707</td>
<td>1.8570</td>
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<tr>
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<td>3.5352</td>
<td>4.4124</td>
<td>4.3255</td>
<td>3.3477</td>
<td>3.7168</td>
<td>5.2095</td>
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<tr>
<td>Image 4</td>
<td>3.1471</td>
<td>3.5857</td>
<td>4.3727</td>
<td>3.6054</td>
<td>3.2087</td>
<td>5.1486</td>
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</table>

### Table 3. WCAG Comparisons

<table>
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<th></th>
<th>WCAG</th>
<th>Real images</th>
<th>Histogram adjustment</th>
<th>Histogram equalization</th>
<th>Wavelet transforms</th>
<th>Homomorphic filter</th>
<th>Our method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>0.0000</td>
<td>0.1902</td>
<td>0.3338</td>
<td>0.1252</td>
<td>0.2008</td>
<td>0.3691</td>
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<tr>
<td>Image 2</td>
<td>0.0000</td>
<td>0.1817</td>
<td>0.2422</td>
<td>-0.0647</td>
<td>0.0967</td>
<td>0.3426</td>
<td></td>
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<tr>
<td>Image 3</td>
<td>0.0000</td>
<td>0.1997</td>
<td>0.1686</td>
<td>0.0092</td>
<td>0.0002</td>
<td>0.3596</td>
<td></td>
</tr>
<tr>
<td>Image 4</td>
<td>0.0000</td>
<td>0.1257</td>
<td>0.3067</td>
<td>0.1872</td>
<td>0.0077</td>
<td>0.3597</td>
<td></td>
</tr>
</tbody>
</table>
Figure 3. Restoration results

For various underwater blurred images, we got the different model parameters. For images shown in Fig.3, they are $k=0.000155$, $k=0.000255$, $k=0.000155$ and $k=0.000155$. So, fixed turbulence model parameter may not be suitable for restore underwater images taken in variable environment. And it should be relevant to the water inherent optical properties. Fig.4 has shown the changes of WCAG in accordance with different $k$. The larger of $k$, the better of restoration results. And reach the optimal performance if $k$ in the 0.00002–0.00004 range. This value can
be treated as a guide value for unknown underwater environment. The qualities of restored images will getting worse as $k$ continue to grow from the optimal value.

Figure 4. The changing of WCAG values of images shown above.

6. Conclusions

In this paper we present an underwater restoration algorithm based on atmosphere turbulence model. This algorithm is automatic and requires no parameter adjustment and no a priori knowledge of the acquisition conditions. This is because functions evaluate model parameter by image quality metric. We have shown that this restoration method greatly enhances the contrast and definition of underwater images and also increase image visual qualities.

7. References


