

Open access • Proceedings Article • DOI:10.1109/OCEANS-YEOSU.2012.6263409

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Published on: 21 May 2012 - OCEANS Conference

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Underwater image quality degradation by scattering

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Abstract— Image quality assessment is a challenging task. Numerous metrics and algorithms have been developed, with a fair share of these efforts focused on referenced targets. For applications associated with most civilian and military needs in the field of intelligence, surveillance, reconnaissance such that automatic target recognition is required, an objective, no reference metric is needed. The task becomes even more challenging when the signals obtained from the imaging sensor are time-varying, including those introduced by the turbulence induced index of refraction fluctuations along the imaging path. This study is aimed to develop an objective metric, tuned to be used for underwater imaging applications where the scattering degradations from particulates, as well as optical turbulence are present. Following recent research outcome, that spatial coherence length is a direct proxy to optical turbulence strength, we developed a metric based on this principle, while including the static scattering contributions with previous developed underwater image quality metric. The results show very good agreement with referenced metric such as the structure similarity image metric, as well as visual, subjective validation, using images obtained from both lab and field experiments.

Keywords-component; image quality; underwater; turbulence; optical scattering

I. INTRODUCTION

Image quality degradation, as a result of imaging systems and environmental factors, is an important topic in research and applications. In this digital age, this is evident, not only with the rapid expansion of digital cameras, scanners, and printers into the everyday life of most households, but also more importantly, in computational vision and ISR (intelligence, surveillance and reconnaissance) applications. Although the term implies a rather broad description of the quality of an image obtained, it is also important to understand the scope of the term and the context it is within. When it comes to image quality, the most common criteria is the sharpness of the image, which represents the ability to present details. Resolutions are typically examined in terms of spatial (angular) frequencies. The contrast of an image 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 [1, 2]. In strong scattering mediums such as those found in medical imaging, atmospheric ISR and stratified clean waters, artifacts and distortions are understandably important parameters in defining image quality as well, but often received little attention in other research areas. The level of noise present in

This project was funded by ONR/NRL Program Element 62782N.

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an image can be critical in certain circumstances, especially when the signal-to-noise ratio is low, or for the purpose of testing different image compression algorithms.

Due to the complexity of the parameters involved, there have been many different approaches, subjectively and objectively, in quantifying the impacts of environmental factors on image degradation. The perceptual image quality is dependent of the individual viewer and so is the value of a metric, but a summation of many opinions often regress to a common ground or a mean opinion score (MOS), which is often used as a benchmark for testing the effectiveness of a metric [3]. Mathematical formulas are developed to quantify these perceptual quality metrics such as the perceptual distortion metric (PDM) [4]. This is generally referred to as a subjective metric where human intelligence and cognition is involved, and is often a function of human visual system. This is understandable, considering the difficulties associated with mimicking human intelligence and vision systems. For example, quality associated with aerial images taken through atmospheric turbulence by a reconnaissance camera will be different from those images taken over a short distance by a camera mounted on a car and only affected by motion blur, or from images taken in a turbid underwater environment such as in an estuary or harbor area. Additional challenges arise when programs are required to make decisions based on incremental image quality variations in minute steps and rapidly changing environments. These issues all affect underwater image quality, and the pressing need is to establish an objective metric that reflects the variations in the quality of the images acquired under these conditions.

A majority research has been done in the area where one compares a degraded image to an ideal version, or reference, to aid algorithm development, such as those in image compression for encoding and transmission. The common approaches in determining the quality include the use of peak signal-to-noise ratio (PSNR) and the mean square errors (MSE) [3]. A structure similarity index metric (SSIM) has been shown to be very sensitive to the image quality variations with known reference [5], including those undergone time-varying influences such as turbulence impacts [6].

Various objective quality metrics exist, independent of the human vision systems, often tuned for specific applications, corresponding to different imaging conditions and impact factors. Such efforts included those that measure the image quality by its sharpness using the gradient or slope of edges [7], by the perceptual blur which measures local blur values based on all edge widths [8], by a variance approach which assumes smoother edges correspond to less variance [9], by the histogram frequency that is associated with non-zero transformed coefficients [10], by the area under MTF to separate high frequency and low frequency contributions [11], via the power spectrum which measures the ratio of high and low frequency energy to the total to reflect details of the image studied [12], and by a wavelet-based perceptual metric that applied a discrete dyadic wavelet transform to obtain edge constraints [13]. The relatively new wavelet transform helps to preserve the edge characteristics, which is especially useful in the situation associated with discontinuities [14].

It is a well-known fact that the major source of degradation, regarding electro-optical (EO) imaging underwater, is from scattering by the medium itself and the constituents within, namely particles of various origins and sizes. Recent research indicates that under certain conditions, the apparent degradation could also be caused by variations of the index of refraction associated with temperature and salinity microstructures in oceans and lakes [15-17]. These would inherently affect optical signal transmissions underwater, which is important to both civilian and military applications such as diver visibility, search and rescue, mine detection and identification, and optical communications. Specifically for underwater imaging, previous studies on image quality degradation have been focused on static degradation due to mostly particles in the water, including those based in point spread models, modulation transfer, and Fourier space [18]. These are adequate, in most cases, to quantify the impacts from the environment, unless temporal variability poses a challenge. Such variations have been observed, in both laboratory and natural environments [16, 17, 19].

In this paper, an improved metric is designed from previous efforts[20], incorporating an unique feature associated with underwater turbulence structures. It is then used in estimation of image quality using lab and field obtained images. These images are also tested against SSIM, which we believe is a first attempt for underwater images. It is encouraging to see the consistency of our new metric, although noise terms seem to be present and need to be addressed in future research efforts.

II. METHOD AND RESULTS

A. Method

The imagery from both the lab and field experiments have been covered in previous publications [17, 21], and the details will not be discussed here. Briefly, a controlled Rayleigh-Benerd convective tank with 5m pathlength was designed and implemented to provide stable optical environments needed. Field imagery was obtained from two exercises in natural lake and oceanic waters[17, 22], along with optical and physical properties quantified. Special care was taken to prevent introducing extra variations, such as those associated with vibrations.

It has been shown that the coherent length (l_0) of the turbulence degraded images are proportional to the optical turbulence intensity, S_n , [17, 22], a coefficient directly related to the opyivsl transfer function (OTF) of the turbulence impact, shown in the form below, including path radiance and particle scattering contributions:

$$OTF(\psi,r)_{total} = OTF(\psi,r)_{path} OTF(\psi,r)_{par} OTF(\psi,r)_{tur}$$
$$= \left(\frac{1}{1+D}\right) \exp\left[-cr + br\left(\frac{1-e^{-2\pi\theta_{0}\psi}}{2\pi\theta_{0}\psi}\right)\right] \exp\left(-S_{n}\psi^{5/3}r\right)$$
$$= \left(\frac{1}{1+D}\right) \exp\left\{-\left[c - b\left(\frac{1-e^{-2\pi\theta_{0}\psi}}{2\pi\theta_{0}\psi}\right) + S_{n}\psi^{5/3}\right]r\right\}$$
(1)

where θ_0 relates to the mean scattering angle, *c* and *b* are the beam attenuation and scattering coefficients respectively. Ψ is the spatial frequency in cycles per radian, *r* is the imaging range, and *D* relates to path radiance [3]. S_n contains parameters that are dependent on the structure function, which can be further expressed in terms of the turbulence dissipation rate of temperature, salinity and kinetic energy, assuming Kolmogorov power spectrum type:

$$S_n \sim \chi \varepsilon^{-1/3} \tag{2}$$

where ε , χ represent the kinetic energy and temperature variance dissipation rates, respectively.

We proceed to test the hypothesis using the coherent length found between individual frames, combined with our previously developed weighted grayscale angle (WGSA) metric [18].

B. Results

Two image sequences converted from video segments were used in this study, both contains strong influences of optical turbulence, with steady (thus static), low level of particle scattering present. The first part was obtained during the Bahamas Optical Turbulence Exercise (BOTEX, June-July, 2011), in optical clean waters. A strong turbulent flow event was captured at the beginning of the 700-frame sequence, followed by a quiet period, and then proceeded to intensify again, although not to the strong level at the beginning of the segment. This was introduced by the index of refraction variation in the middle of a thermocline, at the edge of the Gulf Stream. The second sequence was from a lab environment, where the controlled optical environment with very low level of particles is adjusted using heating and cooling plates. The progressive event showed gradual optical turbulence intensity increase.



Figure 1. Sample underwater images and corresponding SSIM values, from BOTEX experiment (July 2011)



Figure 2. Sample underwater images from controlled environments in the lab via a RB tank, All frames are marked with corresponding frame number and SSIM values.

The SSIM values were calculated for the BOTEX image sequence [22], which is used here to evaluate its effectiveness on underwater optical turbulence, as well as serve as a benchmark to be compared with our newly development metric. The results are shown in Figure 1. The data from the lab experiment are also displayed as a comparison (Figure 2). SSIM algorithm is adopted directly from Wang et al[5]. Notice that only the crop of a collection of sample images are shown to better demonstrate the details. The frame numbers are marked, with SSIM values labeled for each frame. A frame (#500) with weak turbulence impact, thus minimal distortion, is used as a reference (pristine image). This is acceptable, since the optical attenuation due to particle scattering and absorption is rather low (beam attenuation at 532nm is around 0.14m⁻¹[22]). A nearby frame (#501) is shown in Figure 1 and it can been seen as very close in quality (SSIM>0.9). The time series of the SSIM values of the entire segment can be found in Figure 3 (top, 3a). The turbulence intensity variations represented by this short segment can be clearly seen in Figure 3, when SSIM is used as a proxy. While SSIM is known to be a referenced objective metric, it is interesting to observe that by a slight modification in its algorithm, one can use the averaged nearby frames as a reference, to estimate the impacts of turbulence. The results are shown in the lower part of Figure 3 (bottom, 3b), where 3-frame averaged was used. Granted, it does not serve as cleanly an indicator as the referenced approach, shown above. Nonetheless, one should notice that all the low values in Figure 3a are well represented in 3b. This is even more pronounced with a longer average.



Figure 3. SSIM values of individual frames of the segment examined with a known reference frame (Top); SSIM values of individual frames when a 3-frame running averaged is used as the reference frame (bottom).



Figure 4. Comparison between referenced SSIM and our newly developed image quality metric, based on weighted coherency of the image frames. Top (a): SSIM index time series of all frames; Bottom (b): weighted coherency image quality time series for all frames.

From this observation, and the fact that spatial coherency of turbulence degraded images is proportional to its impact intensity, it is therefore reasonable to use an averaged coherency as a proxy to the image quality degradation. A simple cross-correlation can be used to calculate the coherent length [22]. The results are shown in Figure 4. One can clearly see the quality trend shown by SSIM (upper, 4a) is well represented by the newly developed no-reference metric (lower, Figure 4b), especially the first 250 frames. The peak centered around frame #90 is well represented, indicating a quiet period with weak turbulence, while the increased turbulence intensity around frame #30-60 and #130-180 can be clearly seen using both methods. Understandably, the peak representing the perfect match around frame #500 by SSIM (Figure 4a), however, is not captured by our newly developed metric (Figure 4b).

III. SUMMARY

This paper presented a new image quality metric designed to describe underwater image quality degradation caused by both particles and optical turbulence. Two image sequences were used to test and validate its effective. Structure similarity image quality metric is also tested with these images and both approaches demonstrate strong capability in capturing the major events and their impacts on quality degradation. While SSIM performs better in capturing the timing details of the events, it does require a known reference frame, which is not typically available in many field applications. Our newly developed non-reference objective metric, with weighted and averaged coherency showed good agreement to the referenced approach. These encouraging results can be used in assessing image restoration efforts, as well as serving as a feedback in real-time enhancement algorithms, which are currently underway.

ACKNOWLEDGMENT

This research was supported by ONR program element 62782N (NRL base project 73-6369, 73-6604).

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