Improving Quality of Underwater Blurred Images using I.F.M.

Amey Raut, Nikita Kamdi, Yash Tekam, Prof. A.D.Gotmare
Department of CE, BDCE Wardha MH India

Abstract- This paper focuses its attention towards underwater image processing in order to improve the image quality. As most of the images of offshore installations, drinking water reservoir etc. are captured and inspected manually by divers. And manual intervention in this regard is dangerous, costly, time-consuming and yet does not often enable a full assessment. Hence camera based inspection is used to capture the images under water. Using cameras underwater poses major technological challenges. The objects in the underwater images are faint, difficult to view and analyze because the images of such environment loses the details of the object. The underwater images usually suffer from non-uniform lighting, low contrast, skew, blurs and diminished colors. And hence in this research work, a novel method has been proposed for handling underwater image skewing and blurring in case of unidirectional cyclic waves and circular ripples to enhance the visibility of underwater images. The geometric distortion such as skew is caused by the time variant refraction over the dynamic fluids. And this distortion is associated with motion blur depending on the exposure time of camera. The proposed work develops a mathematical model for image restoration from these distortions with good accuracy.

Keywords- underwater, filtering, enhancement, retinex, denoising

I. INTRODUCTION

Camera movements might result in motion blur in captured images. The blurred image is usually modeled as a convolution between the original image and a known point spread function (PSF). Image restoration techniques are used to remove or minimize known degradations in an image. There are several classical image restoration methods, such as the iterative Lucy–Richardson algorithm and the non-iterative Wiener algorithms [1–2]. Several complex methods such as the Bussgang algorithm [3] have also been proposed. In [4], an adaptive restoration method to adaptively correct retinal images is proposed. This is performed by using deconvolution to remove the residual wave-front aberrations and provide an improvement over the Wiener filter with respect to the quality of restoration. An efficient technique based on physical optics is presented in [5]. In this, space-variant blurs are restored by sectioning using modified Wiener filtering. In [6], an image reconstruction and restoration method using the simplified topological ε-algorithm is proposed. In [7], the generalized Hermitian and skew-Hermitian splitting (GHSS) iterative method is applied to the problem of image restoration.

This paper focuses its attention towards underwater image processing in order to improve the image quality. As most of the images of offshore installations, drinking water reservoir etc. are captured and inspected manually by divers. And manual intervention in this regard is dangerous, costly, time-consuming and yet does not often enable a full assessment. Hence camera based inspection is used to capture the images under water. Using cameras underwater poses major technological challenges. The objects in the underwater images are faint, difficult to view and analyze because the images of such environment loses the details of the object. The underwater images usually suffer from non-uniform lighting, low contrast, skew, blurs and diminished colors. And hence in this research work, a novel method has been proposed for handling underwater image skewing and blurring in case of unidirectional cyclic waves and circular ripples to enhance the visibility of underwater images. The geometric distortion such as skew is caused by the time variant refraction over the dynamic fluids. And this distortion is associated with motion blur depending on the exposure time of camera

II. LITERATURE SURVEY

Quality evaluation of underwater images is a key goal of underwater video image retrieval and intelligent processing. To date, no metric has been proposed for underwater color image quality evaluation (UCIQE). The special absorption and scattering characteristics of the water medium do not allow direct application of natural color image quality metrics especially to different underwater environments. Based on these, a new UCIQE metric, which is a linear combination of chroma, saturation, and contrast, is proposed to quantify the nonuniform color cast, blurring, and low-contrast that characterize underwater engineering and monitoring images. Importantly, UCIQE is a simple and fast solution for real-time underwater video processing. This approach[1] extracts the most relevant statistical features that are representative for underwater image degradations such as colour cast, blurring and noise caused by attenuation, floating particles and lighting. This approach uses the following methods (i) defogging based algorithms – to enhance visibility (ii). contrast stretching methods and the newest image fusion enhancement.

By adopting image blurriness with the image formation model (IFM) [2], there is a way to estimate the distance between scene points and the camera and thereby recover and enhance underwater images. This paper used image blurriness to estimate the depth map for underwater image enhancement. It is based on the observation that objects farther from the camera are more blurry for underwater images.

Blurring and low-contrast are the characteristics of underwater images, which are similar to haze images, is the main challenge in searching of fish from underwater images. To overcome the effects of blurring and low-contrast, apply the dark channel prior [3], which was proposed to remove haze from a single input image. Since the underwater images are similar with the haze images, this method mentioned can be also applied to underwater images. The dark channel prior is based on those most local patches in haze-free outdoor images containing some pixels, which have low intensities in at least one color channel. Using this prior with the hazeimaging model, a high quality haze-free image can be recovered. When the dark channel prior is applied to an underwater image, a clear image is generated.

Objects look very different in the underwater environment compared to their appearance in sunlight. High quality images with correct colouring simplify the detection of underwater objects and may allow the use of visual SLAM algorithms developed for land-based robots underwater. Hence, image processing is required to obtain images of high quality and correct colouring. Current algorithms focus on the colour reconstruction[4] of scenery at diving depth which has the advantage that a significant part of sunlight is still present and different colours can still be distinguished. At greater depth the filtering is much stronger such that this is no longer possible. In this study it is investigated whether machine learning can be used to transform image data. In order to obtain images under underwater lighting conditions in a controlled environment a special light source with a defined wavelength is used for illumination of test objects in a laboratory setup. The images are then fed through statistical learning algorithms with or without pre-filters. It is shown that k nearest neighbour and support vector machines are most suitable for the given task and yield excellent results.

Spatial and frequency domain filtering and linear filtering methods are conceptually pleasing and extremely useful in many applications [6]. The spatial filtering is used in spatial domain in the image plane by directly manipulating neighborhood pixels with the help of convolution kernels (Andrews, Hunt, 1987). In frequency domain filtering, if it neglects the presence of interference in the image and restoration is on the footing of the frequency response of correction filter, which was set up for the inverse of the frequency response [7]. This inverse filtering has developed in the frequency domain with the help of FFT. But image restoration by direct inversion was ill-posed owing to the presence of observation noise [8-9]. Direct inversion had caused oscillation due to noise amplification solution [10]. Stephen E. Reichenbach et al. has used corresponding spatial frequency-domain acquisition model. In this model they were designed, small convolution kernels for the restoration of Advanced Very High Resolution Radiometer (AVHRR) images. Small kernels were carried out efficiently by convolution which corrected the degradations and increased apparent resolution of the image. In this restoration, convolution kernels were maximized image fidelity subject to explicit constraints on the spatial support and resolution of the kernel. It was designed with greater resolution than the image to perform partial reconstruction for geometric

III. PROPOSED METHODOLOGY

The proposed work focuses on restoring a static planar scene degraded by skewing effect when imaged through a dynamic water surface. This gets essential because of geometric distortions due to unidirectional cyclic waves and circular ripples in fluid flow. Although the camera and scene are stationary, light rays emanating from a scene undergo refraction at the fluid–air interface. This refraction effect is time varying for dynamic fluids and results in non rigid distortions (skew) in the captured image. These distortions can be associated with motion blur depending on the exposure time of the camera. Hence a mathematical model for blur formation is devised and proposed a restoration scheme using a single degraded observation.

Deblurring and Deskewing of Degraded Image

Estimate the latent image and the set of translational warps using maximum-a-posteriori (MAP) formulation, latent image, PSF from the given blurred observation using sharpening.

Prior on PSF

The PSF for motion blur for camera shake and a sparsity constraint was enforced. The PSF in our scenario represents the set of in-plane translations that any particular pixel experiences due to refraction. The probability distribution of sparse images is heavy-tailed in nature and can be modeled by a Laplacian.

Prior on Latent Image

It is well-known that the gradients of natural images are usually sparse. However, employing a sparse prior will render the latent image estimation problem non-convex. To make our optimization step simpler, we use a Gaussian distribution for image gradients.

Energy Minimization

The latent image and the PSF can by estimated by using an energy minimization approach which minimizes the negative logarithm of the a posteriori probability.

Prediction: The first step is prediction of the latent image estimate l in which the given blurred observation is subject to bilateral filtering, shock filtering and gradient magnitude thresholding. This step ensures that insignificant details and noise are eliminated. The output of this step is an estimate of the gradient of the latent image which is fed as input to the subsequent stages.

PSF Estimation: In this step, we fix the latent image estimate (obtained from prediction) and minimize the energy function

Latent Image Estimation: The latent image is estimated using conjugate-gradient approach. In this step, we fix the PSF obtained from the PSF estimation step and minimize the energy function.

Algorithm 1- for Recovering a Planar Scene Distorted Input

(a) Initial PSF estimate,

(b) single motion blurred image due to water waves

Output: deskewed and deblurred image

1. Repeat
2. Obtain latent image estimate I from prediction step.
3. By using I and initial PSF, estimate PSF
4. By using the estimated PSF, estimate latent image
5. Until maximum number of iterations is reached.

Algorithm 2 - for Recovering a Distorted Scene in the Presence of Circular Ripples Input

(a) Initial PSF estimate

(b) Single motion blurred image due to circular ripples

Output : deskewed and deblurred image

1. Convert blurred observation into polar domain
2. Use algorithm 1 to obtain an estimate of the original image f in the polar domain.
3. Convert the restored image of polar domain back to rectangular coordinates

IV. METHODOLOGY OF THE PROPOSED IFM METHOD

Result Analysis

1. Edge Enhancement using Canny Algorithm

Figure 3.1 shows the flowchart of the proposed method implementation, which begins by decomposing the image color channel. Next, the image histograms are applied with contrast stretching in the RGB color model. Depending on the color channels, the image histograms would be stretched in the upper direction, lower direction, or in both directions. The stretching process is also set to follow the Rayleigh distribution and is limited within a certain range. The image is then converted into HSV color model, in which the S and V components are stretched within the limits of between 1% and 99%. After completing these procedures, the channels are composed, and the image is converted back into the RGB color model. An enhanced contrast output image can then be produced at the final stage. The details process of the proposed method is explained in the next subsections.

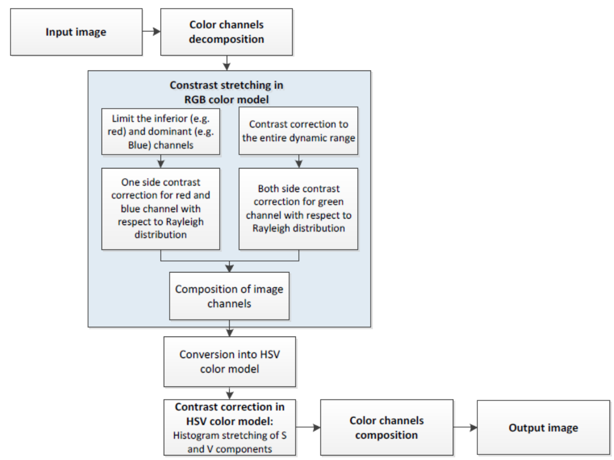
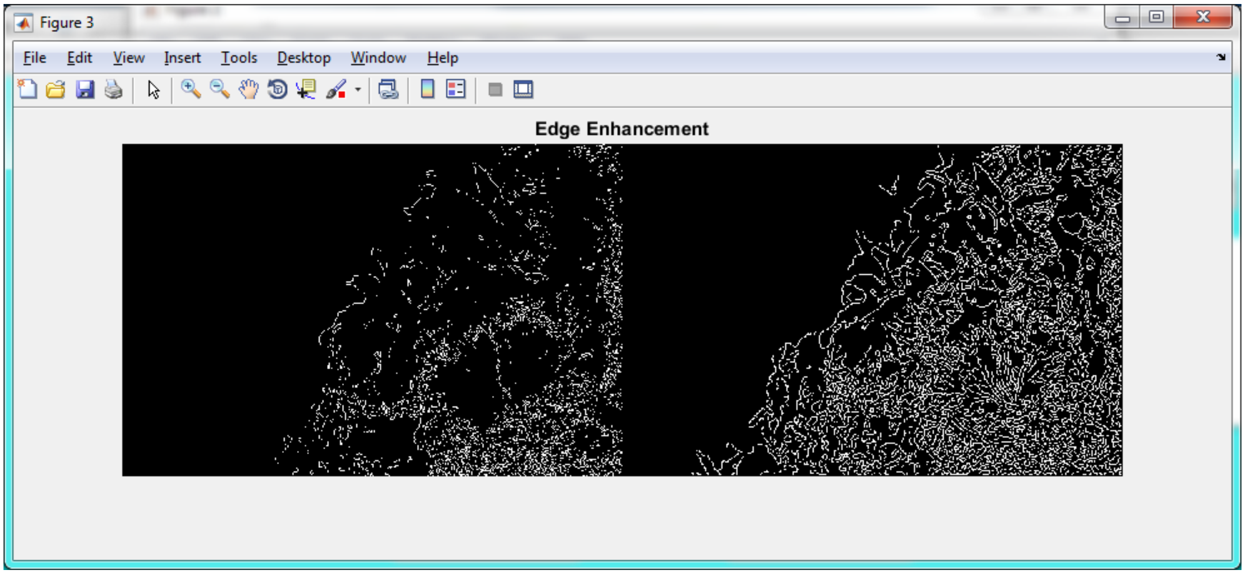
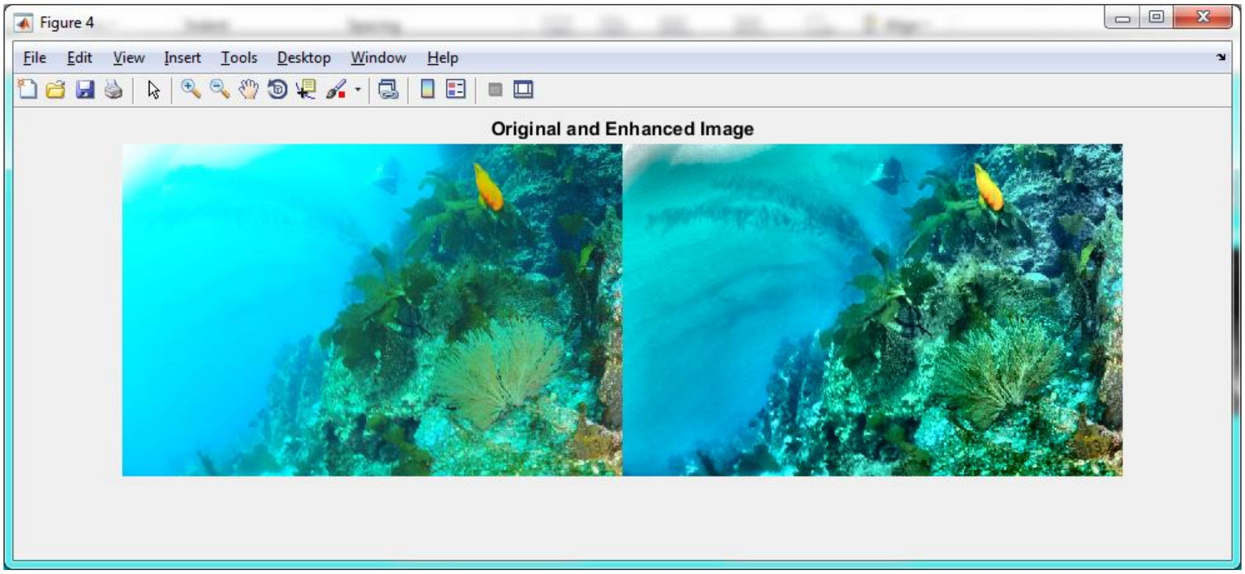


Fig.1: Proposed Methodology



2. RGB Image Enhancement



V. CONCLUSION

A novel method for deskewing and debluring is proposed for distorted images by the dynamic nature of water surface. Existing methods typically need multiple observations to address this problem. In this work, it is possible to perform deskewing and deblurring using a single blurred observation under certain modest constraints on the water flow. Initially, the blur induced is considered as space invariant in nature and proposed a unified framework to deskew and deblur a distorted image..

VI. REFERENCES

[1]. Ancuti, C., Ancuti, C. O., Haber, T., Bekaert, P. 2012. Enhancing underwater images and video by fusion. IEEE International Conference on Computer Vision and Pattern Recognition (CVPR). Providence, RI. 16-21 June 2012. pp. 81-88.

[2]. Anthoni, J. F. 2012. Water and Light in Underwater Photography. http://www.seafriends.org.nz/phgraph/water.htm, excessed on September 2012.

[3]. Arici, T., Dikbas, S., Altunbasak, Y. 2009. A Histogram Modification Framework and Its Application for Image Contrast Enhancement. IEEE Transactions on Image Processing, September 2009, 18(9), pp. 1921-1935.
[4]. Arnold-Bos, A., Malkasse, J. P., and Kerven, G. 2005a. A preprocessing framework for automatic underwater images denoising. Proceedings of the European Conference on Propagation and Systems.
[5]. Brest, France. March 2005. Arnold-Bos, A., Malkasset, J. P., Kervern, G. 2005b. Towards a model-free denoising of underwater optical images. Proceedings of the IEEE Europe Oceans Conference, Brest, France. June 2005. Vol. 1, pp. 527–532.
[6]. Bazeille, S., Quidu, I., Jaulin, L., Malkasse, J. P. 2006. Automatic underwater image preprocessing. Proceedings of the Caracterisation du Milieu Marin (CMM ’06). Brest, France, 16-19 October 2006.
[7]. Foresti, G. L. 2001. Visual inspection of sea bottom structures by an autonomous underwater vehicle. IEEE Transaction on Systems, Man and Cybernetics, Part B, October 2001. 31(5), pp. 691-705.
[8]. Garg, R., Mittal, B., Garg, S. 2011. Histogram Equalization Techniques for Image Enhancement. International Journal of Electronics and Communication Technology, March 2011, 2(1), pp. 107–111.
[9]. Gasparini, F. and Schettini, R. 2003. Color Correction for Digital Photographs. IEEE 12th International Conference on Image Analysis and Processing (ICIAP 2003).
[10]. Mantova, Italy. 17-19 September 2003. pp. 646-651. Gonzalez, R. C. and Woods, R. E. 1992. Digital Image Processing, Addison-Wesley Pub (Sd), Reading, MA, March 1992, 3rd edition.
[11]. Gribbon, K. T. and Bailey, D. G. 2004. A Novel Approach to Real-time Bilinear Interpolation. Proceeding of IEEE International Conference on Field Programmable Technology. 28-30 January 2004, pp. 126-131.
[12]. Hitam, M. S., Yussof, W. N. J. W., Awalludin, E. A., Bachok, Z. 2013. Mixture Contrast Limited Adaptive Histogram Equalization for Underwater Image Enhancement. IEEE International Conference on Computer Applications Technology (ICCAT). Sousse, 20-22 January 2013, pp. 1-5.
[13]. Horváth, G. and Varjú, D. 1995. Underwater refraction-polarization patterns of skylight perceived by aquatic animals through Snell’s window of the flat water surface. Journal of Vision Research, June 1995. 35(12), pp. 1651-1666.
[14]. Hsieh, C. H., Chen, B. C., Lin, C. M., Zhao, Q. 2010. Detail aware contrast enhancement with linear image fusion. IEEE International Symposium on Aware Computing (ISAC). Tainan. 1-4 November 2010. pp. 1-5.
[15]. Huai, X., Lee, K., Kim, C. 2010. Image noise reduction by dynamic thresholding of correlated wavelet intensity and anisotropy. International Conference on SoC Design (ISOCC). 22-23 November 2010. Seoul, pp. 28-33.