Motion Deblurring Analysis for Underwater Image Restoration

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Abstract. Exploration of Underwater Images will be a challenging task due to its degradations by haze, blur, colour cast and noise. In order to extract the latent information from the blurred portion, its parameters are estimated and various algorithms were analysed. Initially, length and angle of motion blurred image are estimated. Then, filters and restoration algorithms were implemented for controlling of ringing artifacts, removal of noise and latent information restoration. Some of the model based classical methods were implemented and analysed for underwater motion blurred image restoration.

1. Introduction
The blur and haze in underwater images are due to the interaction of light with the particles of the medium. The light that reaches the camera requires longer exposure time than using air medium, which results in blur effect. The Gaussian blur due scattering effect degrades the underwater image quality. The quality of an underwater image is necessary for post processing and in turn this evaluates the quality of an image processing algorithm [1]. The most common motion blur occurs in low light areas and is predominant in a moving medium. So to deblur images from cameras [2] proposed a deblurring algorithm using a natural image prior coupled with hardware. This proved to solve the camera motion issue by a joint optimisation using a sampling rate that is very high when exposed in order to deduce the hidden image. Noting the fact that UW blur caused by scattering is dependent on camera-object distance, naturally, spatially variant, compact dictionaries corresponding to different spatial blurriness levels are required. Thereby, a scale-invariant blurriness measure based on sparse representation over a degraded blur dictionary is proposed in [3]. A method to normalise the illumination proposed in [4] achieved deblurring of underwater image by restoration. Based on these [5-8], various underwater deblurring methods were implemented by varying parameters and other factors that estimates and restores the latent information. Even though underwater image processing is an interesting and emerging topic, a very few techniques and algorithms were executed for underwater deblurring. But, various methods are existing for image deblurring than in underwater medium [9-13]. From the surveys of image restoration, motion deblurring seems to be an important underwater research. [14-18] represented the importance and restoration techniques of motion image deblurring. Based on that, underwater motion image deblurring process is analysed in detail.
2. Underwater Optical Turbulence

In lakes and oceans, salinity microstructures and temperature will vary according to index of refraction under certain conditions [19] so; the degraded image impact from optical turbulence was measured with turbulence dissipation rate and optical properties simultaneously. A Simulated underwater turbulence model [20] used the refractive index distribution to obtain various intensities of turbidity. This was used to prove the turbulences responsible for distortion and noise. The suspended and dissolved organic particles caused scattering. The absorption of light beam too caused a reduction in energy. Due to random salinity fluctuations and temperature, the small observable suspended particles will be still inhomogeneous even in clear water. The scene information is assessed with the depth and turbulence. For short exposure images [21] presented simple algorithms to estimate depth and its related measures using turbulences.

3. Underwater Image Degradation

The high resolution underwater optical imaging systems such as the underwater optical cameras with divers, ROV (Remotely Operated Vehicle) and AUV (Autonomous Underwater Vehicle) are used for imaging scenes of short ranges. In this environment, the two fundamental underwater Inherent Optical Properties to be considered are (a) Absorption co-efficient due to the spectral absorbance and (b) volume of scattering function due to scattering per unit distance in the medium. These effects contribute to severe underwater image degradation in forms of color cast, haze, blur and noise. Here, transmission of light in underwater plays a major role. i.e., there are three image formation components namely, Direct Transmission, Forward scattering and Backscattering. These components leads to clear image blur effect and hazy appearance respectively. As per [3], the image formation model is represented as,

\[
g(p, q) = h(p, q) * f(p, q) + n(p, q)
\]  

Where \(g(p, q)\) represents the output, \(f(p, q)\) the input, \(h(p, q)\) being the function representing degradation, \(n\) the noise and \(*\) stands for convolution operation. The transmission component is represented as

\[
E_t = E_d + E_f + E_b
\]

Where \(E_t\) is the total degradation function, \(E_d\), \(E_f\) and \(E_b\) are the direct, forward and backscatter transmission functions respectively. In this forward scattering is responsible for small angle scattering effect which leads to blurry image. The direct component used in the calculation of forward scattering component as

\[
E_d(p, q) = E_d(p, q, 0) * g(p, q | Rc, G, C, B)
\]

\[
g(p, q | Rc, C, A, D) = (e^{-GRS} - e^{-CSR}) F^{-1}(e^{-BRS})
\]

Where, \(Rc\) is camera object distance, \(A\) represents the attenuation coefficient, \(C\) signifies an empirical constant \((|C| \leq A)\), \(D\) symbolises an empirical damping factor, \(F^{-1}\) is the Inverse of the Fourier transform. The sharpness of the edges is the best criteria to indicate the amount of the existing blur in any image. Basically, there are three types of blurs, they are

- **Motion blur**: uniform motion blur caused by camera shaking and Non-uniform motion blur caused by object movement
- **Lens blur**: defocus blur
- **Medium blur**: spatially varying blur caused by medium.
The atmospheric turbulence blur (medium blur) leads to more latent information in the image. It is because of water and its density which leads to scattering. This environment leads to degradation of images with spatially changing blur and haze. Limited depth of field or incorrect lens settings produces defocus blur. Lens blur can be approximately viewed as a spatially invariant due to its diffraction limited blur. Whereas, spatial variance of defocus lens blur depends on depth of scene and field of the lens. On the other hand, Motion blur causes due to the movement of camera or object, camera shake. Fast exposure (shutter speed) could reduce some degree of blur amount. Hence the motion blur is viewed as spatially invariant one, its parameters can be estimated and removed in two ways, blind and non-blind DE convolution. If the PSF is known then the problem can be solved using what are known as image DE convolution techniques, if the PSF is unknown then blind-image Deconvolution must be applied. Blurring is the process which is specified by its point spread function. PSF is a system’s impulse response. In imaging system, it represents the optical transfer function in spatial domain. Important properties of seawater to predict are,

- Underwater light propagation by the Point Spread Function (PSF) and
- Underwater image quality by Modulation transfer function (MTF), Fourier transformed form of PSF.

In order to restore a flawless underwater image, the PSF prior is estimated from [3] as,

\[
g(p, q) = h(p, q) * f(p, q) \quad \rightarrow \quad G(u, v) = H(u, v) * F(u, v) \quad \text{(5)}
\]

\[
H(u, v) = \text{PSF}_{\text{depth}}, \text{PSF}_{\text{water medium}}, \text{PSF}_{\text{optical system}} \quad \text{(6)}
\]

\[
H_{\text{underwater}} = \text{PSF}_{\text{depth}}, \text{PSF}_{\text{spatial domain}}, \text{PSF}_{\text{water scatter}} \quad \text{(7)}
\]

\[
\text{PSF}_{\text{water scatter}} = \exp\{-K(\phi)\} \quad \text{(8)}
\]

Where, \( K(\phi) \) is the decay transfer function for sea waters,

\[
K(\phi) = \frac{i-j(1-\exp(-2\pi\theta_0\phi))}{2\pi\theta_0\phi} \quad \text{(9)}
\]

\( \theta_0 \) being the mean angle, and \( i \) & \( j \) representing the total scattering and attenuation coefficients, respectively.

4. Motion blur

The relative movement between the imaging device and the object causes motion blur. The types of motion blur caused due to luminance spectrum degradation and turbulence in underwater imaging. It is caused by sampling in presence of irregular luminance spectrum. When camera lens refocuses, conventional blur occurs in images due to out-of-focus causing difficulty in identification of motion blur. General, Linear Motion Blur degradation function can be calculated using [3], as

\[
h(p, q) = \begin{cases} 
\frac{1}{L} & \text{if } \sqrt{p^2 + q^2} \leq \frac{L}{2} \quad \text{and} \quad \frac{p}{q} = -\tan(\phi) \\
0 & \text{Otherwise}
\end{cases} \quad \text{(10)}
\]

Where, \( L \) represents motion length and \( \phi \) represents motion direction. By estimating the blur kernel and other blur parameters, the degraded image can be restored. Various restoration techniques were analysed by different authors for motion deblurring as shown in fig.1 and some of them were discussed below.
4.1. Hardware based De-blurring solutions

Three points from blur function can produce space variant PSF. They are,
- Motion sensing of optical image
- Local blur and
- Point spread function of Space variant

Some of the hardware based methods used are,
- Coded aperture:
  - Aperiodic aperture variation to reduce SNR
  - Applied to direct/linear translation
- Dual imager:
  - Faster low resolution imaging device to capture multiple frames while exposure
  - Balance between sensitivity of the sensor and blur restoration
- Inertial Measurement Unit Sensors:
  - Assess platform motion/ PSF with six accelerometer measurements
  - Meticulous scales with object magnification.

System methodology and interfacing- It measures the motion in the image using optical Position Sensing Detector (PSD) along the plane of the image. Produces spatially variant PSF and reconstructs the sharp long exposure images. The actions to reduce motion blur that arises due to system components of position, velocity and acceleration, capturing instant and the PSF.

4.2. Statistical parameters method

The image content and texture are represented using statistical parameters. First, these parameter models are classified into three stages as First order, Second order and Higher order.

First order statistics- This represents the interaction of individual pixel value disregarding the spatial interaction between them. The original image average and variance alone are regarded.
Second and Higher Order Measurements- Here pixel values and their relative positioning are estimated. In this type of statistics, images can also be represented with higher order statistical parameters computed from co-occurrence or run length metrics or from frequented approaches. Histogram based approach considers the intensity value on the whole of the image or a portion. The frequented features comprise of mean, variance, average energy, entropy, dispersion, skewness and kurtosis.

Blind motion deblurring is based on regularization parameter and the number of iterations. The Sparse Gradient Prior eliminates ringing effects and noise. This unavoidably eliminates mid-frequency structures. Even after accurate PSF estimation, the de-convolution algorithm tends to introduce ringing artifacts at boundaries and near strong edges. Some classical method algorithms are used for post de-convolution to reduce ringing artifacts.

5. Results and discussions
Four underwater images are considered from UFO-120 and EUVP datasets. The images of size 500*333 have 166500 pixels. For blur detection and identification of underwater images, parameters like correlation, energy, homogeneity, Skewness, kurtosis and BRISQUE metric is calculated and underwater image quality measures (UIQM) like colourfulness, sharpness and contrast are calculated. Tables 1 and 2 depict degraded images that are in need of restoration.

| S.N | Input Images | BRISQUE | Correlation | Energy | Homogeneity | Skewness | Kurtosis |
|-----|--------------|---------|-------------|--------|-------------|----------|----------|
| 1   |              | 61.210  | 0.927       | 0.268  | 0.946       | -0.77    | 3.33     |
| 2   |              | 60.210  | 0.978       | 0.373  | 0.986       | -1.08    | 6.17     |
| 3   |              | 57.564  | 0.970       | 0.214  | 0.958       | 0.52     | 2.48     |
| 4   |              | 49.535  | 0.967       | 0.205  | 0.936       | -1.14    | 4.16     |
Table 2. UIQM quality measures of input images

| Inputs | UIQM _NORM | COLORFULL | SHARPNESS | CONTRAST |
|--------|------------|-----------|-----------|----------|
| 1      | 1.3057     | 3.1852    | 6.3479    | 0.8745   |
| 2      | 0.6301     | 2.2956    | 2.3160    | 0.4777   |
| 3      | 1.4371     | 6.1506    | 3.2349    | 1.2514   |
| 4      | 1.3004     | 4.3981    | 4.0026    | 1.0527   |

The 3-D representation of PSF and OTF (Optical Transfer Function) for the 1st input image from table-1 is shown in fig.2. This represents the accuracy of PSF also requires reduction of ringing artifacts for latent information retrieval. In order to reduce the ringing artifacts, blur kernel is also to be estimated. Artificial blurring of images usually be (9, 0) as default for length and angle deviation. Even though, the motion blur occurred in underwater medium, it is proved that, when an image is blurred using the same blur function twice, it causes a reasonable damage after the second trial. For blind image de-convolution, PSF are to be estimated accurately, so to estimate the PSF, various higher and lower values of length and angle are applied. The difference of PSF with the image is represented in fig.3. 3.a) shows the blurred image, 3.b) shows reconstructed undersized PSF image, 3.c) shows reconstructed oversized image, 3.d) shows reconstructed true PSF image, 3.e) shows PSF representation of a), b), c) & d). As the image represents, the PSF of various images shows noise and ringing artifacts even when restoring of true PSF.

![PSF and Corresponding OTF](image-url)
Figure 3. a) Blurred image, b) deblurring with undersized PSF image, c) deblurring with oversized PSF image, d) Reconstructed true PSF image, e) PSF of correspond a)-d) images.

Hence the parameter estimation representation for a single image de-blurring shows various blur length & angles, spatial restoration technique may not be the appropriate way for entire image restoration. So, in order to overcome that, frequency domain based estimations are to be performed. By that way, spectrum representation is to be initiated for the input image. Representing frequency spectrum of an image shows the log magnitude. In order to suppress the noise factor in the image, the image is multiplied to ripples. Filtered out image from ripple noise suppression is shown in Fig.4. In fig, the two spikes perpendicular to the periodic noise is zeroed out. After the calculation and estimation of parameters, the deblurring algorithms and techniques can be applied for removing of ringing artifacts and latent information restoration. Some of the classical restoration method like Lucy algorithm, wiener filter, zohair filter, and ALW method are implemented and analysed for motion image deblurring and shown in fig 5, 6, 7 & 8. ALW method gives the output with ringing artifacts but the structures are clearly shown than in input image. Zohair filter too show the structures clearly but with smooth edges. Wiener filter also shows some smooth edges but not clear than the other filtered image. Whereas, Richard Lucy algorithm gives some performance than other three restoration filters. It has the drawback of defocus and medium blur. Deblurred difference is highlighted in Red coloured circle in figure 5-8.

Figure 4. Noise suppression and filtered image from the spectrum
Table 3. Classical Method Output Parameter Evaluation for 1st Input Image

| Methods | Correlation | Energy | Homogeneity | Skewness | Kurtosis | UIQM Norm | Colourfulness | Sharpness | Contrast |
|---------|-------------|--------|-------------|----------|----------|-----------|---------------|-----------|----------|
| ALW     | 0.816       | 0.176  | 0.890       | -0.65    | -0.65    | 3.21      | 1.5955        | 5.0067    | 7.3224   | 1.0956   |
| Zohair  | 0.865       | 0.216  | 0.906       | -0.67    | -0.67    | 3.37      | 1.4678        | 3.8055    | 6.5249   | 1.0317   |
| Weiner  | 0.939       | 0.263  | 0.952       | -0.64    | -0.64    | 3.09      | 1.1924        | 3.3400    | 4.8435   | 0.8739   |
| Lucy    | 0.853       | 0.290  | 0.863       | -0.64    | -0.64    | 3.02      | 1.5195        | 3.4686    | 7.5531   | 1.0058   |

Table-3 shows the output parameter evaluation of 1st input image for some classical motion deblurring algorithms. Though, the analysis shows the similar output for all other input images, only the first input image result is presented. From table-3, the analysis represents that the Lucy algorithm shows better performance when compared to other methods. Though the landweber (ALW) and zohair methods show some optimal results, Lucy’s performance is better for all the parameters considered.
6. Conclusion
The blurred portion and its parameters were studied for the various algorithms. The initial information of length and angle of motion of the blurred images for the filters and restoration algorithms were implemented and presented in the analysis of the algorithms. The values for controlling of ringing artifacts, removal of noise and latent information for the restoration were put forth. Some of the model-based classical methods were implemented and Lucy algorithm seems to give better results. Though the analysis of the various algorithms and the input images was presented, it projected the necessity for colour cast removal considering medium for further effective deblurring. The information based on the BRISQUE values was also incorporated for the study to complement gathering of latent information on blurriness of image.

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