Hybrid Bi-spectrum Multi frame Blind Deconvolution Algorithm for under water image reconstruction

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Abstract

The underwater images are often distorted due to many factors like Frequency Domain, Motion Blur and Refraction Caused by Waves etc... To reconstruct the distorted images there are two methods namely Multi-frame Blind De-convolution (MFBD) & Bi-spectrum Speckle Imaging (SI). A new technique is proposed called Hybrid Bi-spectrum Multi frame Blind De-convolution (B-MFBD) by taking the advantages of both the methods. The proposed method involves both SI and MFBD techniques. In proposed method, to start the iterative image reconstruction, the MFBD makes use of the output of a bi-spectrum SI estimator. The two existing techniques suffer from slow convergence, by using new method i.e., Hybrid Bi-spectrum MFBD technique that can be overcome. Proposed technique gives a high speed and better performance compared to bi-spectrum SI and multi frame blind de-convolution (MFBD) methods of image reconstruction.

Keywords: Bi-spectrum, speckle imaging (SI), MFBD, Hybrid B-MFBD

Introduction

The images taken under water are affected by many surrounding and geographical factors. These images are suffered from blurring, distortion and quality degradation. When underwater object is captured from outside the water, waves on the surface causes distortion. If more number of pictures is taken at various times, in each pictures we can see different distortion. Hence data acquisition for constructing the images is difficult and it affects on the image construction. Image reconstruction affects mainly on the image quality. Image is constructed by using the acquired data. Image reconstruction is an inverse process and it leads to some unwanted artifacts in the image. Image blur and noise are the problem while forming the image from the acquired data. Hence image deblurring and denoising are necessary. The existing methods are iterative in nature and they segment the image into multiple tiles. Though the multiple tiling of the image gives high speed, this leads to artifacts. Hence to overcome these artifacts an efficient algorithm is required.

I. MFBD (Multi-frame Blind De-convolution) Technique

The MFBD is image reconstruction method it uses multiple frames of noisy and blurry observations to calculate the phase information, object amplitude and blurring function, starts with object guess. It considers image distortion and additive noise as a single parameter represented as $n_k(\vec{p})$. The parameter can be expressed as in equation 1.

$$d_k(\vec{p}) = i_k(\vec{p}) + n_k(\vec{p}) = \sum_{\vec{q}=\vec{0}}^{\vec{e}} o(\vec{q})h_k(\vec{p}-\vec{q}) + n_k(\vec{p}) \quad (1)$$
$$\text{with } \vec{p} = (x, y) \text{ a point in the image.}$$

Where, $d_k(\vec{p})$ = captured input image frame
K = frame of the image.
$\vec{p}$ = point in the image i.e., (x, y).
$i_k(\vec{p})$= captured image(noise free version) at point $\vec{p}$
$O(\vec{q})$ = distribution of object intensity at point $\vec{q}$
$h_k(\vec{e})$ = point spread function (PSF) of Zernike coefficients.

The Gaussian Probability Density Function (PDF) is a random variable for each image at each point p of a gaussian model.
The PDF can be expressed as in equation (2)

$$p[d_k(\vec{p})] = \frac{1}{\sqrt{2\pi\sigma_n^2}} \exp\left(-\frac{|d_k(\vec{p}) - i_k(\vec{p})|^2}{2\pi\sigma_n^2}\right) \quad (2)$$

For all points of image, the product of PDF of $d_k(\vec{p})$, as joint density function is given by :

$$L(\vec{o},\vec{\alpha}) \equiv L(\vec{o},\vec{h}) = -\sum_{k=1}^{K}\sum_{\vec{p}=\vec{0}}^{\vec{e}} |d_k(\vec{p}) - i_k(\vec{p})|^2$$
$$= \sum_{k=1}^{K}\sum_{\vec{p}=\vec{0}}^{\vec{e}} |d_k(\vec{p}) - \sum_{\vec{q}=\vec{0}}^{\vec{e}} o(\vec{q}) h_k(\vec{p}-\vec{q})|^2 \qquad (3)$$

Objective function's gradient over the pixel intensities is expressed as,

$$\frac{\partial}{\partial\vec{o}} L(\vec{o},\vec{\alpha}) = -2\sum_{k=1}^{K}\sum_{\vec{p}=0}^{\vec{e}} |d_k(\vec{p}) - i_k(\vec{p})| \frac{\partial}{\partial o(\vec{p})} i_k(\vec{p}) \qquad (4)$$

Substituting $i_k(\vec{p})$ from (1) into (4), we obtain,

$$\frac{\partial}{\partial\vec{o}} L(\vec{o},\vec{\alpha}) = -2\sum_{k=1}^{K}\sum_{\vec{p}=\vec{0}}^{\vec{e}} |d_k(\vec{p}) - i_k(\vec{p})| \sum_{\vec{q}=\vec{0}}^{\vec{e}} h_k(\vec{p}-\vec{q}) \qquad (5)$$

In the same way, the objective function's gradient over the Zernike coefficients $\vec{\alpha}_k$ is expressed as,

$$\frac{\partial}{\partial\vec{\alpha}} L(\vec{o},\vec{\alpha}) = -2\sum_{k=1}^{K}\sum_{\vec{p}=\vec{0}}^{\vec{e}} |d_k(\vec{p}) - i_k(\vec{p})| \frac{\partial}{\partial\vec{\alpha}_k} i_k(\vec{p}) \qquad (6)$$

So, the objective function's gradient can be expressed as

$$\nabla L(\vec{o},\vec{\alpha}) = \frac{\partial}{\partial\vec{o}} L(\vec{o},\vec{\alpha}) + \frac{\partial}{\partial\vec{\alpha}} L(\vec{o},\vec{\alpha}) \qquad (7)$$

The maximization of the cost function is involved in the MFBD technique. To optimize the Cost function the limited memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) iterative algorithm is used.

LBFGS algorithm's input is a combination of the initial set of Zernike coefficients $\vec{\alpha}_0$ and image reconstructed through the bi-spectrum SI technique $\vec{o}_0$. Using the most recent *m* values of $\vec{c}_t$ and its gradient $\nabla_t L(\vec{c})$ a new updated form of $\vec{c}_t+1 = \vec{c}_t + \Delta\vec{c}_t$ is obtained in the *t*-th iteration of LBFGS.

II. Bi-spectrum SI Algorithm

Fourier phase of target image is recovered by using Bi-spectrum SI technique. By using the Fast Fourier transform (FFT) phases in the input image, the DC frequency bins are found.

The image Represented by equation (8) is a observed image that is the convolution of the object intensity distribution [o(x)] of the point spread function [s(x)].

I(x) = s(x)*o(x) (8)

The Equation (9) as Fourier transform of i(x) is given below:

Algorithm 1: LBFGS Algorithm

Definitions
$\vec{s}_t = \vec{c}_{t+1} - \vec{c}_t$
$\vec{w}_t = \nabla_{t+1} L[\vec{c}] - \nabla_t L[\vec{c}]$
$\rho_t = \frac{1}{\vec{w}_t^T \vec{s}_t}$
Set values for μ_1, μ_2, m, and j
for j *iterations* **do**
  Step 1:LBFGS algorithm
  Initialize the LBFGS algorithm
  $\vec{q} = \nabla_t L[\vec{c}]$
  for $i = t-m, t-m+1, .., t-1$ **do**
    $\gamma_i = \rho_i s_i^T \vec{q}$
    $\vec{q} = \vec{q} - \gamma_i \vec{y}_i$
  end
  $\mathcal{H} = \vec{w}_{t-1}^T \vec{s}_{t-1} / \vec{w}_{t-1}^T \vec{w}_{t-1}$
  $\vec{q} = \mathcal{H}\vec{q}$
  for $i = t-1, t-2, .., t-m$ **do**
    $\beta_i = \rho_i \vec{w}_i^T \vec{q}$
    $\vec{q} = \vec{q} + \vec{s}_i(\gamma_i - \beta_i)$
  end
  Step 2: Line search algorithm
  Initialize the line search algorithm
  Set initial value for ζ_t
  while $(L(\vec{c}_t + \zeta_t\vec{q}) - L(\vec{c}_t) > \mu_1\zeta_t\vec{q}^T\nabla_t L(\vec{c}_t))$ *or* $(\vec{q}^T\nabla_t L(\vec{c}_t + \zeta_t\vec{q}) < \mu_2\vec{q}^T\nabla_t L(\vec{c}_t))$ **do**
    Update ζ_t
  end
  $\vec{c}_{t+1} = \vec{c}_t + \zeta_t\vec{q}$
end

I (u) = S(u)O(u) (9)

The mean power spectrum of the FFT of the image is given as in equation 10.

$$\left\langle |I(u)|^2 \right\rangle = \left\langle |S(u)|^2 \right\rangle |O(u)|^2 \simeq |\langle I(u)\rangle|^2 + N_S T(u) |O(u)|^2, \qquad (10)$$

The unknown phases can be recovered from equation (11) from the bi-spectrum

$$\exp(j\varphi(\vec{f}+\Delta\vec{f})) = \exp(j\varphi(\vec{f})) \times \exp(j\varphi(\Delta\vec{f})) \times | \exp(-j\varphi_B(\vec{f},\Delta\vec{f})) \qquad (11)$$

Where,

The Equation (8) is computed and to obtain a good estimation of the object phase at each spatial frequency, average is found for sufficient number of paths (multiple values of $\Delta\vec{f}$) and *'B* ($\vec{f}$, $\Delta\vec{f}$) is a bi-spectrum phase of $\vec{f}$ and $\Delta\vec{f}$. And *'*($\vec{f}$) is the object's Fourier phase.

III. Related Work

The various studies have been carried out on the image reconstruction. The literature survey involves the study of the existing techniques and their outcome.

The tiling technique can speed up the performance of the system and the image can reconstruct properly without any data loss [1] U.R. Acharya.

The author S. Ashwin has used a technique Dark channel prior that also darkens the image and removes the noise and haze that was caused by bluish surroundings. They have used CLAHE- Contrast limited adaptive histogram equalization upon RGB images that improves the intensity and the brightness of an image. The experiment results were objectively and subjectively had favorable outgrowth that effectively monitors the scenario of underwater [2].

In this work performance analysis is done for mean square error (MSE) value of the image. J. P. Bos and speckle imaging method is used instead of multi frame ensemble average too initialize the MFBD algorithm [3, 4].

The author A. Ceballos surveys the methods and enhances the filtered sequence of underwater based images on quality metrics. It balances the brightness with homomorphic filter technique that improves the lighting by CLAHE and enhanced by bilateral filters. The results showed an improvement in brightness, sharpness of edges and color [5].

The author Charles L. Malton demonstrates the measurability of parallelization over the distributed computer memory nodes, with the outcome associated with the Cramer-Rao lower level bounds. It mainly concentrates on the image restoration with ground based telescopes data [6].

The author Dibya Jyoti Bora makes an effort to examine and analyze the various enhancement methods and selecting one best algorithm for segmenting an image based on color. The study is carried out on color spaces such as HSV and LAB distinctively to evaluate which color space assist segmentation more effectively regarding to enhancement methods [7].

In this the author Glen E. Archer compares the Mean square error –MSE execution of speckle image techniques with MFBD- Multiframe blind de-convolution, that is applied on longest path of horizontal image underneath anisoplanatic recognized condition. From these two methods the images are reconstructed, and comparison results display the reduction in MSE -47% with SI techniques but MFBD techniques gives a 40% enhancement in MSE with same conditions. The execution of MFBD estimator and hybrid bi-spectrum which employs Rapid Bi-spectrum estimation is examined for MFBD reconstruction method [8].

In the work carried out by author S. Hajmohammad, the two loop version of the LBFGS algorithm is discussed in detail. Thus the slow convergence can overcome by proposed hybrid B-MFBD algorithm. The advantage of the proposed algorithm is that it produces a same image quality or better than the pure MFDM even for a small number of iterations and frames [9,10,15].

The author J.L Harvill proposes a method that distinguishes different non linear series in time and also time series between the linear and non linear employing a hierarchical method of clustering with distance calculation with the help of square modulus with evaluated formalized bi-spectra. This method estimated average ration of formalized bi-spectral period gram. It was robust choosing smoothing limit that estimates bi-spectrum [11].

The author PROF.S.V. Halse proposes different techniques for reconstructing and enhancing an image that improves the quality of an image. The enhancement of image improves the content of data of image, also alters the impact of visualization of image of an observer. This gives different pre-processing techniques that increase the quality of image [12].

The author A.V Kanaev demonstrates techniques for restoring of underwater images which are immensely degraded by turbulence of underwater. This approach derives the structure of a tensor images with quality metrics that incorporates a lucky patch framework image processing. It is guided by the local strength of an edge and orientation highlights are compared to an unsuccessful restoration. This utilizes a standard isotropic metrics [13].

The work carried out by R.Linderman focuses on the PCID multi-core effort. This involves the alteration of the Physically-Constrained Iterative De convolution (PCID) algorithm optimized to enhance performance This method involves the clustering process whereas the present work focus on the parallelization by tiles or frames [14].

The author U.A Nnolim employs upgraded underwater images enhanced methods that are related on partial differential equations- PDEs. These experiments shows improved evidences compared to previously used approaches with the other conventional method [16].

The author Omkar .G. Power presents a novel approach that enhances the underwater images by using distant factor evaluation including the dehazing method and equalization of histogram of images. The pre-processing is carried out to remove the noise with distant factor related to intensities of various color images enhancing the contrast of dimmed images [17].

The author Shrinivas Shirkande concentrates on submerged images upgraded quality by analyzing the previous research works. Wavelength compensation and image dehazing –WCID and wavelets transform to enhance the submerged images quality is proposed [18].

The author V. K. Sudarshan considers a flexible optimization approach that can easily incorporate prior information and various filtering schemes resulting in a scheme that is more tractable computationally in this paper. The studies on the MFBD algorithm show that the better value reconstruction can be obtained from the MFBD compared to bi-spectrum SI But the MFBD suffers from slow convergence [19].

IV. Proposed Method

The proposed work involves the parallelization of both the SI and MFBD algorithm. The block diagram is as shown in figure1.

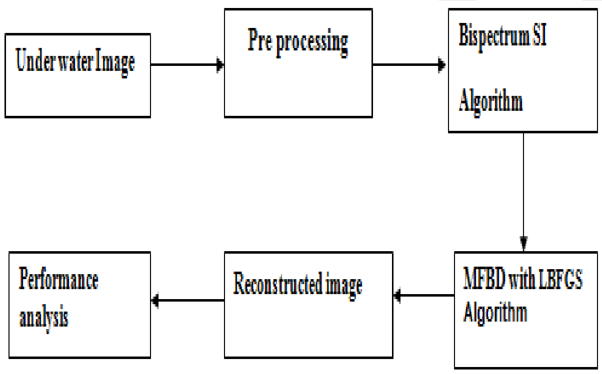


Figure 1: Block diagram of the hybrid B-MFBD technique.

The under image is taken as the source for image reconstruction. The RGB image is taken as input. The preprocessing involves the conversion of RGB image into gray scale image to reduce the complexity and computation time. The zero padding of the image is done to avoid edge effects. The Gaussian noise with zero mean and variance V is considered [7]. The bi-spectrum SI and MFBD are the iterative methods of image reconstruction. Using Single Program Multiple Thread (SPMT) computing fabric of MPA of GPU, the computational complexity of the proposed method is decreased by parallelization. In two steps the parallelization is performed. Step one involves the parallelization of the MFBD where LBFGS algorithm plays a important role in optimizing the cost function and the step two is bi-spectrum SI parallelization[8] J. P. Bos. After performing the parallelization we get the reconstructed image. Further the performance analysis can be done by finding Mean Square Error (MSE) and Peak Signal to Noise ratio (PSNR) values of the image[9] J.L. Harvill. The complete design flow is as shown in figure 2.

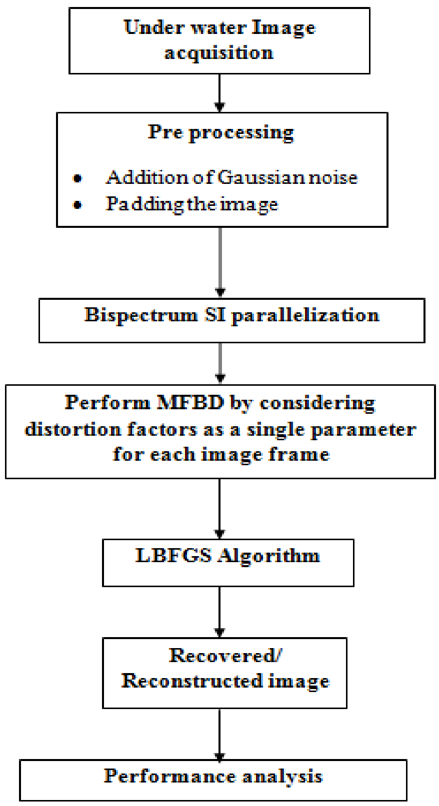


Figure 2: Flow diagram of the Proposed Hybrid Bi-spectrum MFBD technique

The steps involved in the Parallelization techniques can be obtained from section1 where the explanation of the algorithms is explained in detail.

V. Results of Experiment:

We have used Matlab, R2014a, 64-bit for the experimental set up. The RGB image of size 256x256 is considered for experimental purpose.

The results obtained are as shown in the following figures below.

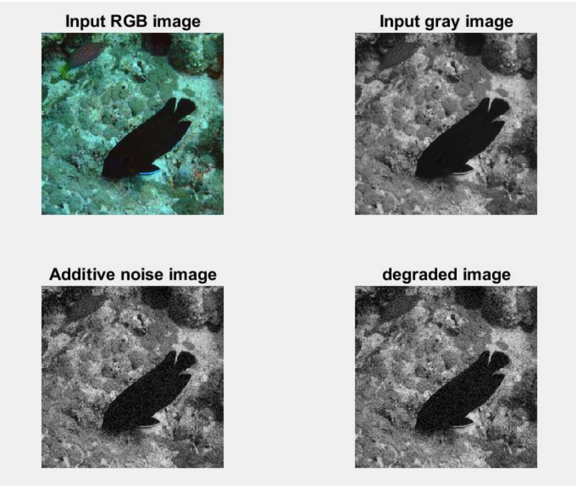


Figure 3: (a)Input RGB image,(b) Converted Grayscale image of RGB image, (c) Image with Gaussian noise added, (d) Under water degraded image.

The results of Bi-spectrum algorithm are as shown in figure 4 to figure 6.

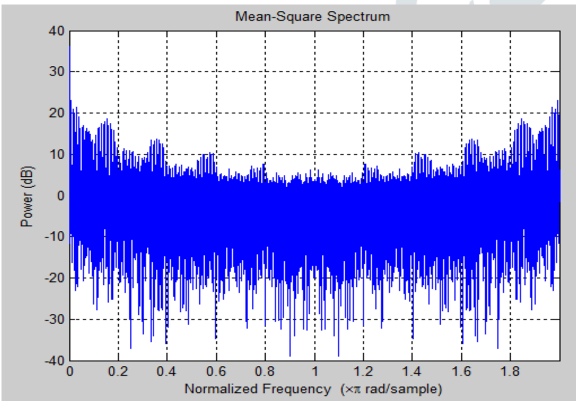


Figure 4: Power spectrum of the image

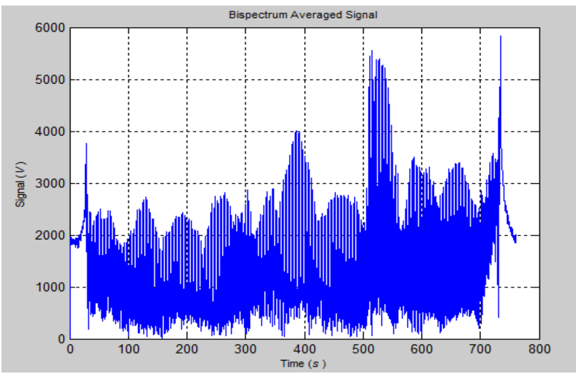
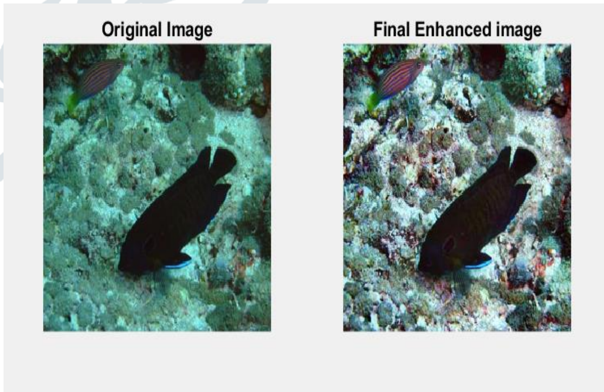


Figure 5: Bi-spectrum of the image with phase and amplitude

Figure 6: The reconstructed Bi-spectrum image

The reconstructed image of MFBD algorithm is as shown in figure 7

Figure 7: The reconstructed MFBD image



The PSNR and MSE values of the various images are tabulated as in Table1 below.

	BiSpectrum	Hybrid BiSpectrum
PSNR	55.42356	64.3734
MSE	0.15623	0.023754
Entropy	0.8943	0.92341

Table2: Optimization of Bispectrum:

Iteration	Func-count	f(x)	Step-size	First-order optimality
0	1	19.2074		0.54
1	3	10.1747	5.24873	0.262
2	5	10.0001	0.28012	0.00568
3	6	10	1	6.85e-05
4	7	10	1	3.64e-10

VI. Conclusion:

The work carried out proposes a Hybrid B_MFBD algorithm for under water image reconstruction. To start the iteration, the output of the parallelization of bi-spectrum SI is followed by MFBD technique. The better performance is given by proposed hybrid Bi-spectrum MFBD algorithm than the only bi-spectrum SI and MFBD algorithms that is shown in experimental results. The performance analysis of the image is done by means of PSNR and MSE values. The PSNR and MSE parameters are calculated for various underwater images. The proposed work computation speed is no loss in under water image quality and more with less execution time.

VII. References

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