Adaptive Bacterial Foraging Optimization Based Restoration and Degradation using chromatic adaptation transforms

Rekha Rani, Pawan Kumar

***Abstract*— Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. Bacterial Foraging Optimization (BFO) is a recently developed nature-inspired optimization algorithm, which is based on the foraging behavior of E. coli bacteria. The adaptive bacterial foraging optimization ABFO employs the adaptive foraging strategies to improve the performance of the original BFO. This improvement is achieved by enabling the bacterial foraging algorithm to adjust the run-length unit parameter dynamically during algorithm execution in order to balance the exploration/exploitation trade off. This process is carried out up to a certain number of steps, which is limited by the lifetime of the bacteria.**

***Index Terms*—Adaptive bacterial foraging optimization, Bacterial Foraging Optimization, chromatic adaptation transforms, Image Restoration**

I. INTRODUCTION

To understand the implementation of Biogeography Based Optimization, Firstly have to understand some terms that are discussed given below:

A. Image Restoration

Image Restoration refers to a class of methods that aim to remove or reduce the degradations that have occurred while the digital image was being obtained. Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as motion blur, noise, and camera misfocus. The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. Degradation comes in many forms such as motion blur, noise, and camera misfocus. In cases like motion blur, it is possible to come up with an very good estimate of the actual blurring function and "undo" the blur to restore the original image. In cases where the image is corrupted by noise, the best we may hope to do is to compensate for the degradation it caused. In this project, we will introduce and implement several of the methods used in the image processing world to restore images. Image restoration is different from *image enhancement* in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) provided by "Imaging packages" use no a-priori model of the process that created the image.In image restoration the information provided by the microscope is only taken as indirect evidence about the object. By itself the image needs not even to be viewable.

- A microscopic image contains more information than is readily visible in the image.
- Often, details are hidden in the noise or masked by other features.
- Artifacts may confuse the viewer.
- Information may be present in implicit form so it can only be retrieved with the addition of a-priory knowledge.

A general model of a simplified digital image degradation process

A simplified version for the image restoration process model is

$$y(i,j) = H[f(i,j)] + n(i,j)$$

where

$y(i,j)$ the degraded image

$f(i,j)$ the original image

H an operator that represents the degradation process

$n(i,j)$ the external noise which is assumed to be image-independent

We see in the figure below a schematic diagram for a generic degradation process described by the above simplified model.

II. IMAGE RESTORATION TYPES

Bacterial Foraging Optimization (BFO) is a recently developed nature-inspired optimization algorithm, which is based on the foraging behaviour of *E. coli* bacteria. Up to now, BFO has been applied successfully to some engineering problems due to its implicity and ease of implementation. A variation on the original BFO, called the adaptive bacterial foraging optimization ABFO, employing the adaptive

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foraging strategies to improve the performance of the original BFO. This improvement is achieved by enabling the bacterial foraging algorithm to adjust the run-length unit parameter dynamically during algorithm execution in order to balance the exploration/exploitation tradeoff. In adaptive delta modulation the error or the deviation between the actual signal and the modulated signal is integrated and the output of the integrator is fed in a voltage controller that controls the step size. Here, X is the parameter to be optimized to obtain the desired value D. $F(X(i, j))$ denote the cost function of X of ith bacterium in jth chemotactic step. $E(j)$ denotes the deviation from the desired value. $S(i, j)$ is the step size which is modified in each chemotactic step depending on the deviations in the previous steps. The multiplier increases or reduces the step size accordingly. Parameter X for next step is obtained by adding the step size with the previous value. The proportional adder can be replaced by individual gains in the paths of errors. Here we have taken the deviations in last three chemotactic steps and their sum is multiplied with the previous step size. The ABFO algorithms
have markedly superior search performance when compared to the original BFO, while maintaining the similar or even superior performance compared to PSO and GA in terms
of accuracy, robustness, and convergence speed on all benchmark functions. The proposed ABFO1 and ABFO2 described in this paper enhance previous BFO works in the following aspects:

1. A new adaptive strategy, namely, the producer-scrounger foraging, to dynamically determine the chemotactic step sizes for the whole bacterial colony during a run, hence dividing the foraging procedure of artificial bacteria colony into multiple explore and exploit phases;
2. A new self-adaptive foraging strategy, namely, the area concentrate search, to respectively tune the chemotactic step size for each single bacterium during its run, hence casting the bacterial foraging process into heterogeneous fashion;
3. A comprehensive study comparing ABFO1 and ABFO2 with another two state-ofthe- art global optimization algorithms, namely, GA and PSO, on high dimensional functions;
4. Single and colonial bacterial behaviours in both ABFO1 and ABFO2 that were simulated respectively in order to analyze in depth the adaptive and self-adaptive foraging schemes in the proposed models;
5. New results on benchmark functions up to 300 dimensions

$(t \quad n = \ )$

$f \quad < \varepsilon(t))$

$C(t + \ ) = C(t \quad n)/\alpha$

$\varepsilon \ (t + \ ) = \varepsilon(t)/\beta$

$C(t + \ ) = C(t \quad n)$

$\varepsilon \ (t + \ ) = \varepsilon \ (t-n)$

$C(t + \ ) = C(t)$

$\varepsilon \ (t + \ ) = \varepsilon \ (t)$

In the initial phase, the bacteria colony searches the whole space of the problem with a large run-length unit Cinitial_here, the same run-length unit is used for all bacteria its all the bacterial producers to explore the whole space efficiently and avoid being trapped in local optima. This dynamic adaptive strategy is given in Pseudocode 1. Where t is the current generation number, $f$best is the best fitness value among all the bacteria in the colony, $\varepsilon\_t\_$ is the required precision in the current generation, and n, α, and β are user-defined constants. Using this strategy, changes in the parameter values of C are now based on feedback from the search, and the adaptation happens every n generations.

III. Literature Survey

There exist number of nonblind or classical image restoration techniques like Inverse Filtering, Wiener filter etc but it has some drawbacks.

Howard Kaufman and A. *Murat Tekalp*has proposed Inverse filtering classical image restoration technique. It was developed by Nathan in 1966 to restore images. It is also known as convolution. Inverse of PSF was used to recover image. Inverse filtering can be efficiently implemented in frequency domain using FFT but deconvolution by direct inversion was ill - posed .The advantage of the inverse filter is that it requires only the blur PSF as a priori knowledge but drawback is noise amplification.

D. A. Fish, A. M.*Brinicombe, and E. R. Pike* have presented a blind deconvolution algorithm based on the Richardson–Lucy deconvolution algorithm. It was developed from Baye's theorem. In this algorithm initial guess is required for the object to start algorithm. Then after that in subsequent iteration large deviation in the guess from true object are lost rapidly in initial iteration whereas detail is added more slowly in subsequent iteration.

Benoit's (1997) image restoration theory is used to examine the image restoration strategies used by BP in response to the oil spill. Image restoration theory provides researchers and practitioners with a practical framework to assess how effective in the public's eyes BP was in maintaining its corporate image. Image restoration strategies are often used after a crisis when an organization is trying to address the public.

Lindlof and Taylor (2011) qualitative approaches "study human symbolic interaction in the various contexts of its performance" (p. 4). As the purpose of this study was to understand which image restoration strategies are used in the post-crisis stage, a qualitative approach was appropriate. Qualitative seeks thick, rich descriptions of a phenomena rather than quantifiable, generalizable data.

IV. Design and Implementation

To implement Adaptive Bacterial Foraging Optimization Based Restoration and Degradation using chromatic adaptation transforms. The main stages are the following main stages:
Input: Original image

To restore the local motion-blurred part of an image is a very complex process. In order to restore the image better, the main ideas are as follows: First, the blurred part is extracted from the complex background and pasted on the bottom of monochromatic background. Then a restorative process is done on the blurred image in the monochrome background which is easy to restore. Finally, the restored part is pasted back to the original complex background.

A. The restoration algorithm includes following ones:

1. Extracting the edge of the blurred image from the original one;
2. Pasting the blur image onto a black bottom;
3. Removing the background color interference in the blurred image;
4. Restoring the blurred image in the black bottom using the physical principle of image blur;
5. Pasting the restored image back onto the original background;
6. Restoring the background color interference to the original background

Then consider the general degradation model

$$y(i,j) = H[f(i,j)] + n(i,j)$$

If we ignore the presence of the external noise $n(i,j)$ we get

$$y(i,j) = H[f(i,j)]$$

H is***linear*** if

$$H[k_1 f_1(i,j) + k_2 f_2(i,j)] = k_1 H[f_1(i,j)] + k_2 H[f_2(i,j)]$$

H is***position*** (or ***space***) ***invariant*** if

$$H[f(i-a, j-b)] = y(i-a, j-b)$$

From now on we will deal with linear, space invariant type of degradations.

B. Implementation of BFO based on Chromatic Transform

[Step 1] Initialize parameters *p, S, Nc, Ns, Nre, Ned, Ped, C(i)(i=1,2…S)*,*i*q .

Algorithm:

[Step 2] Elimination-dispersal loop: *l*=*l*+1

[Step 3] Reproduction loop: *k*=*k*+1

[Step 4] Chemotaxis loop: *j*=*j*+1

[a] For *i*=1,2…S take a chemotactic step for bacterium *i*as follows.

[b] Compute fitness function, *J (i, j, k, l)*.

Let, *J* (*i*, *j*, *k*, *l*) *J* (*i*, *j*, *k*, *l*) *J* ((*j*, *k*, *l*),*P*(*j*, *k*, *l*)) *i*

cc = + q (i.e. add on the cell-to cell attractant–repellant profile to simulate the swarming behavior) where, *Jcc*is defined in (2).

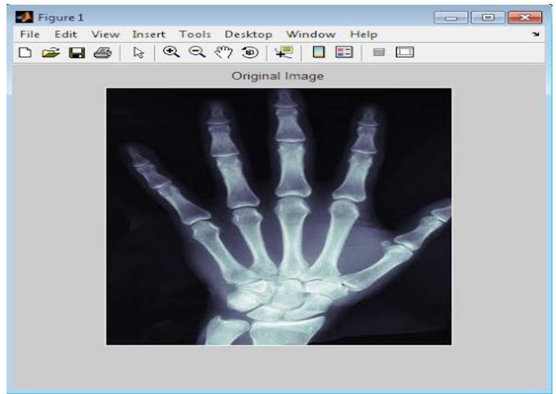
[Step 5] If *c j* <*N* , go to step 4. In this case continue chemotaxis since the life of the bacteria is not over.

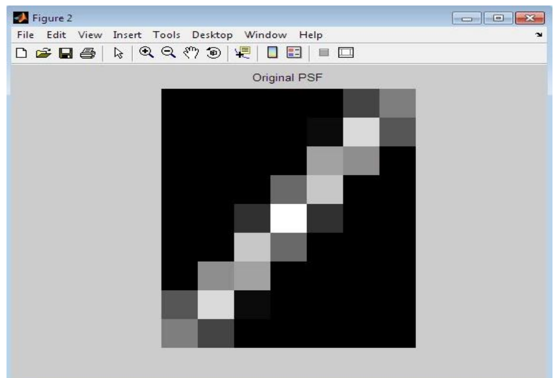
[**Step 6**] If *re k* <*N* , go to step 3. In this case, we have not reached the number of specified reproduction steps, so we start the next generation of the chemotactic loop.

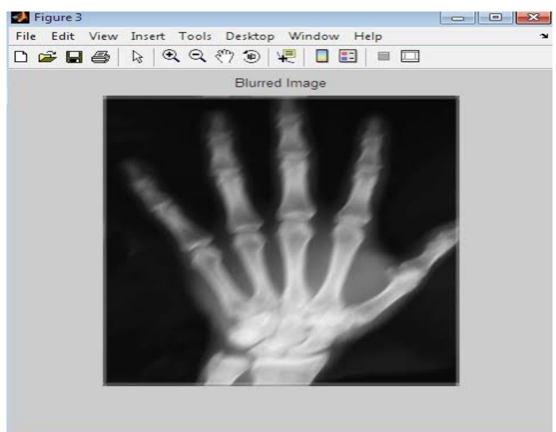
[**Step 7**] Elimination-dispersal: For *i*= 1,2..., *S* with probability *ed P* , eliminate and disperse each bacterium (this keeps the number of bacteria in the population constant). To do this, if a bacterium is eliminated, simply disperse another one to a random location on the optimization domain. If *ed l* <*N* , then go to step 2; otherwise end.

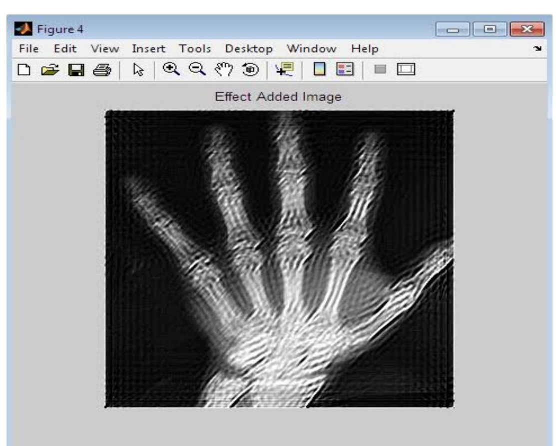
B.Output: Produce Resorted image

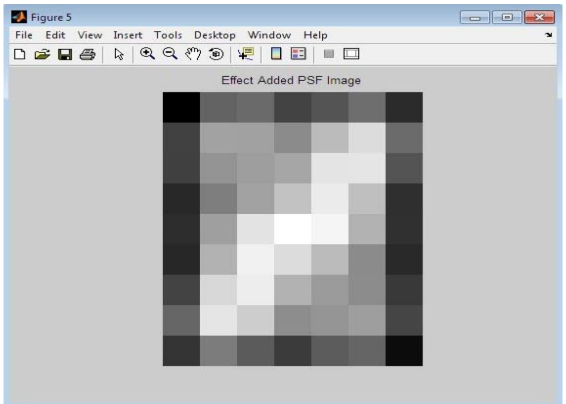
V. RESULTS AND DISCUSSIONS

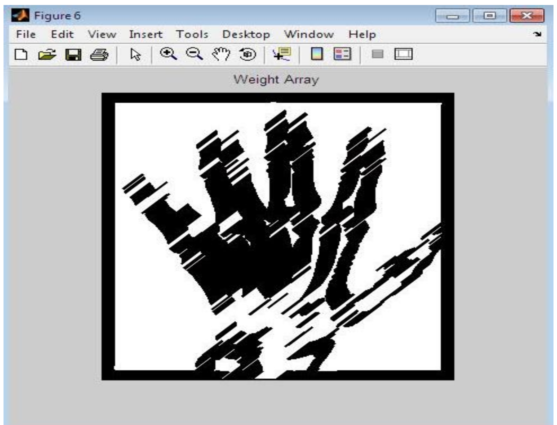


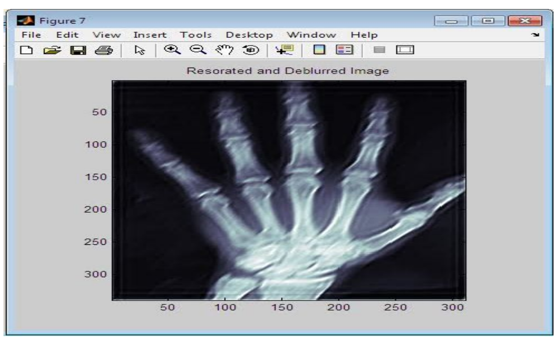












CONCLUSION AND FUTURE SCOPE

Color images allow for more reliable Image restoration gray scale images. Image Restoration aim to remove or reduce the degradations that have occurred while the digital image was being obtained. As concluded, Biogeography Based Optimization is more reliable and fast search algorithm for Image Restoration purposes. Biogeography Based Optimization generally results in better optimization results than the Genetic Algorithm for the problems that we investigate. A group of bacteria move in search of food and away from noxious elements — a biological method known as foraging. All bacteria try to move upward the food concentration gradient individually. At the initial location they measure the food concentration and then tumble to take a random direction and swim for a fixed distance and measure the concentration there. This improvement is achieved by enabling the bacterial foraging algorithm to adjust the run-length unit parameter dynamically during algorithm execution in order to balance the exploration/exploitation tradeoff. This process is carried out up to a certain number of steps, which is limited by the lifetime of the bacteria.

REFERENCES

[1] Mariana S. C. Almeida and Luís B. Almeida, “Blind and Semi-Blind Deblurring of Natural Images,” IEEE transactions on image processing”, vol. 19, no. 1, January, 2010.

[2] Jian-Feng Cai , Hui Ji , Chaoqiang Liu , Zuowei Shen, “Blind motion deblurring using multiple images,” Department of Mathematics, National University of Singapore, Singapore, 117542, March 4, 2010.

[3] Lu Yuan1 Jian Sun2 Long Quan2 Heung-Yeung Shum2, “Image Deblurring with Blurred/Noisy Image Pairs,” the Hong Kong University of Science and Technology. Pawar and Wagh 170.

[4] Howard Kaufman and A. Murat Tekalp, “Survey of Estimation Techniques in Image Restoration, ” Jan 1991.

[5] Reginald L. Lagendijk and Jan Biemond, Information And Communication Theory Group, Faculty of Technology, the Netherlands, “Basic methods for image restoration and identification,” February, 1999.

[6] D. A. Fish, A. M. Brinicombe, and E. R. Pike, “Blind deconvolution by means of the Richardson–Lucy algorithm,” Department of Physics, King’s College London, Strand, London WC2R 2LS, UK and J. G. Walker, Department of Electrical and Electronic Engineering, University Park, University of Nottingham, Nottingham NG7 2RD, UK, J. Opt. Soc. Am. A/ Vol. 12, No. 1/January 1995.

[7] DeepaKundur, Student Member, IEEE, and DimitriosHatzinakos, Member, IEEE, “ Novel Blind DeconvolutionScheme for Image Restoration Using Recursive Filtering,” IEEE transactions on signal processing, VOL. 46, NO.2, FEBRUARY 1998.

[8] In Jae Myung*, “ Tutorial on maximum likelihood estimation,” Department of Psychology, Ohio State University, 1885 Neil Avenue Mall, Columbus, OH 43210-1222, USA Received 30 November 2001; revised 16 October 2002

[9] DeepaKundur and DlmltrlosHatzinakos, “Blind image deconvolution,” IEEE signal processing magazine, May 1996 .

[10] M.Mattavelli, G.Thonet, V.Vaerman, B.Macq, “Image restoration by 1D Kalman filtering on oriented image decompositions, ” IEEE 1996 .

[11] S. DerinBabacan, Variational Bayesian Blind DeconvolutionUsing a Total Variation Prior, 12 IEEE Transactions On Image Processing, Vol. 18, No. 1, January 2009.

[12] Feng-qing Qin, Blind Image Super-Resolution Reconstruction based on PSF estimation, Department of Computer and Information Science University of Yibin, Proceedings of the 2010 IEEE International Conference on Information and Automation, June 20 - 23, Harbin, China.