Slami SAADI[1], Abderrezak GUESSOUM[1], Maamar BETTAYEB[2]

University Saad Dahlab of Blida (1), Sharjah University (2)

Regularized Total Variation Image Enhancement Using E.Coli Bacteria Foraging Algorithm: Application to Neutron Radiography Projections

***Abstract**. This paper proposes a novel approach based on swarm intelligence and foraging behavior of Escherichia coli Bacteria in the human intestine for enhancing neutron radiography projections blurred during acquisition by the high neutron flux and noise contaminated due to Gamma radiations. This approach uses the total variation (TV) optimization to solve an ill-posed problem. We consider a regularization operator for smoothing task. In comparison with other efficient methods, the proposed Algorithm can be suitable for image enhancement and noise removal.*

***Streszczenie.** W artykule zaproponowano wykorzystaniu algorytmu rojowego bazującego na zachowaniu bakterii E.coli do poprawy jakości projekcji radiograficznej. W porównaniu z innymi algorytmami ta metoda charakteryzuje się dobrą możliwością poprawy jakości obrazu i usuwania szumu. (**Poprawa jakości obrazu radiograficznego przy wykorzystaniu algorytmu bazującego na bakterii E.coli**)*

Keywords: E.Coli Bacteria Algorithm, Neutron Radiography, TV, Regularization
Słowa kluczowe: obraz radiograficzny, poprawa obrazu, algorytm rojowy.

Introduction

Image enhancement is a mandatory preprocessing step in the analysis of any kind of images. By image restoration, we seek to recover the original sharp image using a mathematical model of the blurring process. The key issue is that some information on the lost details is indeed present in the blurred image, but this information is “hidden” and can only be recovered if we know the details of the blurring process. Due to various unavoidable errors in the recorded image, we cannot recover the original image exactly. The most important errors are fluctuations in the recording process and approximation errors when representing the image with a limited number of digits [1]. The image restoration techniques are widely used in various applications. In this work, we implement a tool for neutron radiography gray level images restoration and enhancement.

We can generally classify restoration techniques into two classes: the filtering reconstruction techniques and the algebraic techniques. The filtering techniques make use of the fact that noise signals usually have higher frequencies than image signals. This means that image signals die out faster than noise signals in high frequencies. Examples of the restoration filters are the deconvolution filter, in which the transfer function of the degraded system is inverted to produce a restored image, and the Wiener filter that uses the mean-squared error (MSE) criterion to minimize the error signal between the original and degraded images. In [2] they used this filter in 2D case for digital image restoration. The linear algebraic techniques utilize matrix algebra and discrete mathematics for solving the problem of image restoration. Regularized deconvolution can be used effectively when constraints are applied on the recovered image (e.g., smoothness) and limited information is known about the additive noise. Optimization methods can be used to solve a large-scale constrained linear least-squares optimization problem. Authors in [3] did a comparative study of four optimization algorithms based on simulated annealing: the Gibbs Sampler, the Metropolis algorithm, the Iterated Conditional Modes, and a random descent method. In [4] they made use of some formulas from the theory of basic hyper geometric series to deblur images degraded by a modified Gaussian blur. A simple and fast deblurring algorithm for Gaussian has recently presented in [5] in which they solved the ill-posed problem of backward heat equation by truncation of a Neumann’s expansion of the backward heat operator followed by a forward heat operator to stabilize the procedure. Authors of [6] proposed an approximate Singular value decomposition (SVD) as a direct method. In [7] the restoration problem is modelled as an optimization problem and they used the genetic algorithm for gray images restoration. In [8] a new anisotropic diffusion model is proposed for image restoration and segmentation, which is closely related to the minimization problems for the unconstrained total variation. Stack filters that are non-linear spatial operators used for noise suppression have been formulated in [9] as an optimization problem solved by genetic algorithm for restoring magnetic resonance images corrupted with uncorrelated additive noise. General variational model for image restoration based on the minimization of a convex functional of gradient under minimal growth conditions has been discussed in the paper [10]. A novel method called edge-preserving regularization is presented in [11]. This method is used to solve an optimization problem whose objective function has a data fidelity term and a regularization term; the two terms are balanced by a parameter λ. A recent work in [12] improved the total variation model introduced by Rudin, Osher and Fatemi in 1992 in order to preserve the textures and eliminate the staircase effect by proposing a class of fractional-order multi-scale variational models for image denoising. They conclude that this is more flexible than R-O-F model.

Most of the optimal techniques that have been proposed in literature over the past few decades to solve such problem by iterative optimization procedures are computationally demanding and time consuming. We tested several image deconvolution algorithms for this purpose and conclude that total variation algorithms can obtain preferable results. But these iterative algorithms face the difficulties associated with noise amplification. After a number of iterations, the restored image can have a speckled appearance, especially for a smooth object observed at low signal-to-noise ratios. In [13] we employed Particle Swarm Optimization (PSO) Algorithm with regularization constraints to reconstruct motion blurred neutron radiography projections and we got excellent results (taking the PSNR as a metric). A new swarm intelligence Algorithm based on the E.coli bacteria foraging behavior was introduced by in [14], and during the last years, many propositions appeared to improve the classical BFO Algorithm, which have accelerated its convergence and enhanced its searching precision. Authors of [15] and [16] propose a new variant of BFO which employs linear dynamically decreasing chemotaxis run-length step parameter. A BFO Algorithm with varying population (BFAVP) is presented in [17], which incorporates a varying population framework and the underlying mechanisms of bacterial chemotaxis, metabolism, proliferation, elimination and quorum sensing. Results show that this modification performs better than other Evolutionary Algorithms in terms of both accuracy and convergency.

The newly contribution in this paper is the introduction of this novel emerging swarm optimization Algorithm in order to smooth the progress of optimization process in TV regularized method to obtain a restored image from a hardly degraded image in a hostile medium (neutron radiography near a horizontal channel of a nuclear reactor). These results are so close to results obtained using the universally known methods.

Image Degradation

The degradation process is modelled as a blurring function H(x,y) that, together with an additive noise term η(x,y), operates on an original input image f(x,y) to produce an observed degraded image g(x,y),Fig.1:

(1) $$g = Hf + \eta$$

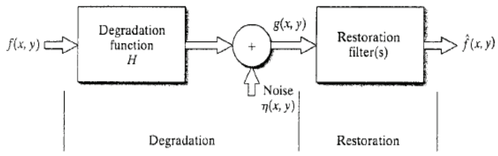

Fig.1: Simplified model for image degradation/restoration process

Given g(x,y), some knowledge about H(x,y)and η(x,y), the objective of restoration is to obtain an estimate of the original image f(x, y). We want the estimate to be close as possible to the original input image. Blurring can arise from many sources, such as limitations of the optical system, camera and object motion, astigmatism, and environmental effects.

In addition to blurs, observed images are usually contaminated with noise. Noise can arise from several sources and can be linear, nonlinear, multiplicative or additive.

Tikhonov Regularization

The main objective of regularization is to incorporate more information about the desired solution in order to stabilize the problem and find a useful and stable solution. The most common and well-known form of regularization is that of Tikhonov [18]. The Tikhonov regularized minimum norm solution of equation (1) is the vector $F_\delta \in \Re^N$ that minimizes the expression:

(2) $$\|Hf - g\|_2^2 + \lambda^2 \|Lf\|_2^2$$

Where λ>0 is called a regularization parameter. We denote:

(3) $$F_\delta = \arg\min_x \left\{ \|Hf - g\|_2^2 + \lambda^2 \|Lf\|_2^2 \right\}$$

Regularization can be understood as a balance between two requirements:

f should give a small residual *Hf - g* .

f should be small in *L2* norm.

The regularization parameter λ>0 can be used to "tune" the balance. Note that in inverse problems there are typically infinitely many solutions *f* satisfying (3).

Total Variation Regularization

Total variation (TV) is often used for image filtering and restoration. Total variation based filtering was introduced by Rudin, Osher, and Fatemi [19]. They introduced in 1992 the following idea:

Instead of minimizing: (4) $$\|Hf - g\|_2^2 + \lambda \|Lf\|_2^2$$

Let us minimize: (5) $$\|Hf - g\|_2^2 + \lambda \|Lf\|_1$$

Recall that: $\|Z\|_2^2 = |Z_1|^2 + \ldots + |Z_N|^2$

and: $\|Z\|_1 = |Z_1| + \ldots + |Z_N|$

The idea is that (5) should allow occasional larger jumps in the reconstruction leading to piecewise smoothness instead of overall smoothness.

Many algorithms have been proposed to implement TV filtering. The most famous one is by Chambolle [20]. The derivation in this algorithm is based on the min-max property and the majorization-minimization procedure.

Bacterial Foraging Optimization Algorithm (BFO)

Foraging means locating, handling, and ingesting food. Animals that have successful foraging strategies are favored since they obtain enough food to enable them to reproduce, so they are more likely to enjoy reproductive success [21]. This has led scientists to model the activity of foraging as an optimization process. Authors of [14] explain the biology and physics underlying the chemotactic (foraging) behavior of E.coli bacteria (the ones that are living in your intestines), and give a computer program that emulates the distributed optimization process represented by the activity of social bacterial foraging and apply that in adaptive controllers.

The foraging strategy of E. coli bacteria can be explained by four processes namely: Chemotaxis, Swarming, Reproduction and Elimination/Dispersal [14].

We want to find the minimum of *f(x),* $x \in \Re^p$, where we do not have measurements or an analytical description of the gradient $\nabla f(x)$. Here we use ideas from bacterial foraging to solve this non gradient optimization problem. First, suppose that *x* is the position of a bacterium and *f(x)* represents the combined effects of attractants and repellents from the environment, with *f(x)<0*, *f(x)=0*, and *f(x)>0* representing that the bacterium at location x is in nutrient-rich, neutral, and noxious environments, respectively. Bacteria try to climb up the nutrient concentration (find lower and lower values of *f(x),* avoid noxious substances, and search for ways out of neutral media).

BFO Algorithm:

1.Initialization: We choose p, S, N_c *,* N_{re} *,* N_{ed} *,* P_{ed} *and the C(i), i=1,2,…,S. for swarming, we choose also parameters of the cell-to-cell attractant functions. Initial values for* θ^i *,i=1,2,…S are also chosen.*

2.Elimination-dispersal loop: l=l+1

3.Reproduction loop: k=k+1

4.Chemotaxis loop: j=j+1

a) For i=1 to S take a chemotaxis step for bacterium I as follows.

b)Compute f(i,j,k,l) and let:

$f(i,j,k,l) = f(i,j,k,l) + f_{cc}(\theta^i(j,k,l), P(j,k,l))$ *,we add on the cell-to-cell attractant effect to the nutrient concentration.*

c) Let f_{last} *= f(i,j,k,l) to save this value since we may find a better cost via a run.*

d) Tumble: generate a random vector Δ(i) $\in \Re^p$ *with each element* $\Delta_m(i)$*, m=1,2,…P, a random number on [-1,1].*

e) Move let:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

this results in a step of size C(i) in the direction of the tumble for bacterium i.

f) Compute f(i,j+1,k,l), and then let:

$$f(i,j+1,k,l) = f(i,j+1,k,l) + f_{cc}(\theta^i(j+1,k,l), P(j+1,k,l))$$

g) Swim: let m=0 and While m<N_s put m=m+1,if f(i,j+1,k,l) < f_{last} let f_{last} =f(i,j+1,k,l) and let:

$$\theta^i(j+1,k,l)=\theta^i(j+1,k,l)+C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

and use this position to calculate the new cost value.
Else, let m=N_s end while.
h) Go to the next bacterium.
5. if j<N_c then go to step 4.
6. Reproduction: For i=1,2,…,S

$$f^i_{health} = \sum_{j=1}^{N_c+1} f(i,j,k,l)$$

i) Sort bacteria and chemotactic parameters C(i) in order of ascending cost f_{health} (higher cost means lower health). The S/2 bacteria of the highest cost will die and the healthiest are placed at the same location as their parent.
1. if k<N_{re} go to step 4.
2.Elimination-dispersal: for i=1,2,…,S, with probability P_{ed} , eliminate and disperse each bacterium.
3. if l<N_{ed} then go to step 1, otherwise end algorithm.

Simulation Results

We established a new approach used to solve a constrained optimization ill-posed problem. We corrupted images of different sizes using many types of degradation functions and noises, and then try to restore the original. Our starting image is a gray-level image contained in a *mxn* matrix. Each element in the matrix represents a pixel's gray level between black and white (0 and 255) [13]. The simplest approach is to solve the least squares problem:

(6) $$\min(\|h\otimes f-g\|_1)$$

where $\otimes$ is the convolution operator

In practice the results obtained with this simple approach tend to be noisy, because this term expresses only the fidelity to the available data *g*. To compensate for this, the below regularization term is added to improve smoothness of the estimate:

(7) $$0.004\bullet\|Lf\|_1$$

L is the discrete *Laplacian*, which relates each data element to its neighbors. *L* is a 2-D discrete approximation of:

(8) $$l=\frac{\nabla^2 X}{2N}=\frac{1}{2N}\left(\frac{d^2X}{dx^2}+\frac{d^2X}{dy^2}\right)$$

where *X* is the estimated matrix. The matrix *L* has the same size as *X* with each element equal to the difference between an element of *X* and the average of its four neighbors. Since we know we are looking for a gray intensity, we also impose the constraint that the elements of *X* must fall between 0 and 255. To obtain the deblurred image, we want to solve for *f*:

(9) $$\min(\|h\otimes f-g\|_1+0.004\bullet\|Lf\|_1$$

We can implement our objective function using this expression; the number of variables in this function to be minimized will be $m\times n$ which is the size of the matrix representing the original image. We run the algorithm using Intel Pentium4 PC with 1.80GHZ CPU and 1Go memory size. The average processing time is dependent upon computation machine, image size and choice of E.coli algorithm parameters (varies from few seconds to few minutes). Some simple images, created by the MATLAB function *checkerboard* of sizes: 8x8, 16x16, 32x32, 64x64, 128x128 and finally 256x256 pixels, are used (this test image contains all gray levels starting from 0 to 255), before using real gray-level images got from neutron radiography. With different BFO algorithm parameters as follows:

The number of bacteria: s=6,10,20,30,50,80;
Number of chemotactic steps: Nc=10,20,30,50,70,80,100;
Limits the length of a swim: Ns=10,20,30,40,50,70,80,100;
The number ofreproduction steps: Nre=10,20,30,40,50,70,80,100;
The number of elimination-dispersal events: Ned=1;
The number of bacteria reproductions (splits) per generation: Sr=s/2;
The probability that each bacteria will be eliminated/dispersed: Ped=0.25;
The run length: c(i)=0.05;

To quantitatively judge the quality of several BFO parameters combinations, we recorded in Table1 for blurred/noisy images the sensitivity of the BFO algorithm with parameters variations in terms of MSE, PSNR and objective function minimum. A full statistical analysis of these results for tuning parameters is accomplished by applying ANOVA test (analysis of variance) [22]. We use a 4-Way ANOVA with a Large Data Set (8x8, 16x16, and 64x64) and with random effects as a statistical test of whether or not the means of several groups are all equal to illustrate the statistical significance of the tuned parameters, Table 2. The expected value of each mean square depends not only on the variance of the error term, but also on the variances supplied by the random effects.

We focus on the four parameters: *S, Nc, Ns and Nre*, for the four example sizes: 16x16, 64x64, 128x128 and 256x256 pixels. For the run-length parameter *C(i)*, authors of [14] observed that a better performance would be obtained if a reasonable *C(i)* value were chosen. When we choose large run length, the bacteria will have an exploring ability (the bacteria are swimming without stop missing the global minimum) while choosing relatively small run length will make the bacteria have exploiting skills (take a long time to reach the global minimum). Hence, we can fix this parameter to a medium value (0.05) for all *s* bacteria to make a compromise between accuracy and speed of search.

Table 1: Sensitivity analysis for E.coli Algorithm with varying parameters: Restoring Blurred/Noisy Image with Regularization

	RMSE	PSNR	Cost Function
Degraded Image	0.57	52.99	
S=6	0.12	68.37	2.2035
S=10	0.12	68.44	2.2909
S=20	0.10	68.75	2.2270
S=30	0.11	68.43	2.2090
Nc=10	0.18	66.84	8.0116
Nc=20	0.12	67.67	3.2706
Nc=30	0.11	68.52	2.2263
Nc=50	0.10	68.02	2.1670
Nc=70	0.10	68.02	2.1670
Ns=10	0.11	67.53	2.6089
Ns=20	0.10	68.22	2.3635
Ns=30	0.10	67.94	2.4871
Ns=50	0.10	68.52	2.2263
Ns=80	0.10	68.52	2.2263
Nre=10	0.30	58.53	20.8247
Nre=20	0.19	62.41	9.0574
Nre=30	0.14	65.06	4.5166
Nre=50	0.10	68.28	3.0948
Nre=80	0.09	68.75	2.2270
Nre=100	0.11	67.94	2.3504

Although it is very difficult and almost impossible to tune the best set of parameters, it is very important that a reasonably effective set of these parameters is determined, so that the deblurred image quality is accepted enough for use. We can select the best bacterial foraging parameters in Table 3. This selection is based on a compromise between restored image quality and expense in terms of both time and computational resources. The objective function evolution through reproduction steps is also showed in Fig.2.b.

Table 2: The ANOVA TABLE for Restoring Blurred/Noisy Image

The ANOVA Table				
Sources of Variation	Sum of Squares	Degrees of Freedom	Mean Squares	F-Statistic
Between Groups	0.141	3	0.0470	3.065
Within Groups	0.184	12	0.0153	
Total	0.325	15		

Restoration of a checkerboard test gray level image blurred and noised together with and without regularization constraint is presented in Fig.3 and Fig.4.

Table 3: Best E.coli Algorithm parameters for restoring blurred/Noisy images with regularization (Best Regularization parameter is 0.004)

Parameters	Values
S	6
Nc	70
Ns	30
Nre	70
Ned	1
Sr	S/2 =3

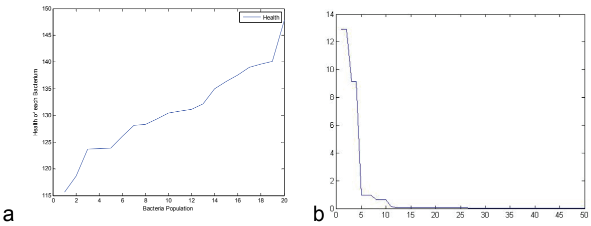

Fig.2: a) Health of each Bacterium in Ascending Order, b) Cost function evolution through 50 reproduction steps

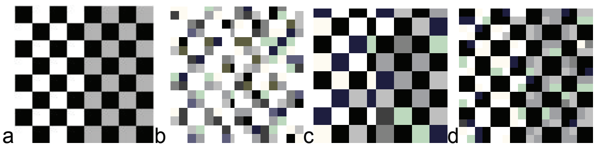

Fig.3: Restoration of Blurred Images using E.coli Algorithm with Regularized TV: a)Original, b)Blurred, c)with p=8x8 d)with p=16x16

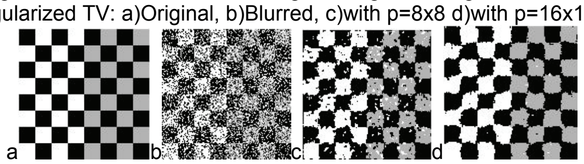

Fig.4: Restoration of Noised Image using E.coli Algorithm with Regularized TV: a)Original, b)Noised, c)with p=8x8 d)with p=16x16

In the following, we have selected four state of the art methods used for image restoration: Truncated Singular Value Decomposition (TSVD), Tikhonov regularization, normalized Tikhonov in Sobolev space and Total Variation (TV) regularization solved with iterative recursive least squares method. For TSVD, the truncation parameter used in simulation is 4e-3. Tikhonov regularization used here is feasible by direct computation for such inverse problem using the Kronecker product structure, regularization parameter found as the used in simulation is 4e-5. The second Tikhonov regularization is an approximation of the popular Sobolev seminorm penalization, regularization parameter found as the best used in simulation is 1e-5. In (TV), regularization parameter found as the used in simulation is 4e-3.

In Fig.5 we present the restoration of a *checkerboard* test image (a) that has been blurred with motion blur function and noise is added (b). Three methods of restoration: linear inversion filter (c), FFT with zero padding in frequency domain (d) and TSVD (e). In the TSVD, the condition number *cond(A)* = σ_1 / σ_N was found to be 7.337638 x 10^4. With Tikhonov (f), with ROF (g) and finally with Chambole Algorithm. In Table 4 we recorded the corresponding RMSE and PSNR for each method compared to BFO Algorithm.

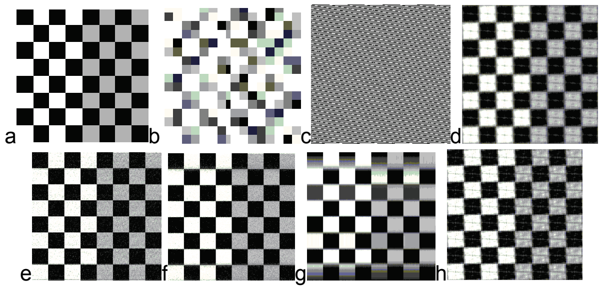

Fig. 5: Restoration some classical methods, a)Original, b)Blurred, c)Inverse Filter, d)FFT and zero padding, e)TSVD, f)Tikhonov, g)ROF, h)Chambole

Table 4: Restoration comparison using four classical techniques

	RMSE	**PSNR**
Degraded	0.57	52.99dB
TSVD Restoration	0.08	69.86 dB
Tikhonov Restoration	0.06	71.92 dB
Tikhonov (sobolev) Restoration	0.12	66.83 dB
TV Regularization Iterative Least Square Restoration	0.24	60.41 dB
E.coli Algorithm Restoration	0.09	68.75dB

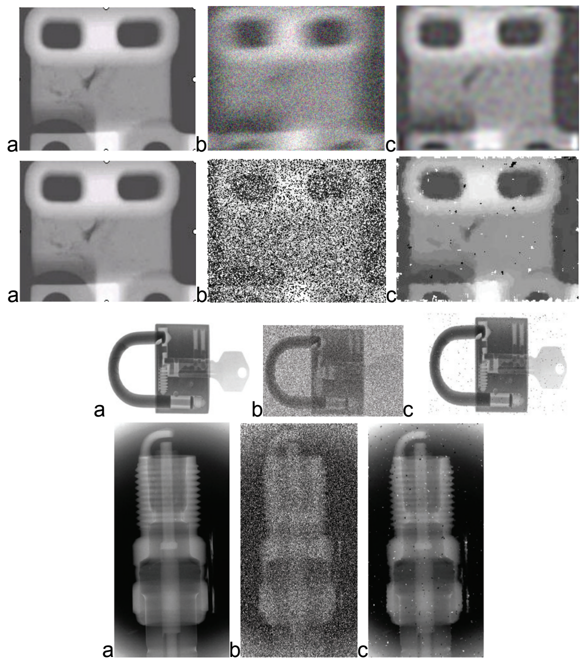

Fig.6: Neutron Radiography Image restoration using E.coli Algorithm with Regularized TV: a)Original, b)Blurred/Noisy, d)Restored

Neutron Radiography Image Enhancement:

Digital radiological image is acquired by a certain radiological procedure. It is a two-dimensional *MXN* array of non-negative integers (gray levels). For neutron radiography, the gray level value represents the relative linear attenuation coefficient of the object [23]. Each of these gray images has 8-bit representations of their intensity levels. Hence, there are 256 gray levels. Degradations in this imaging technique are essentially due to bad situation with respect to randomly distributed neutron flux causing dissimilarity in images taken for the same object, in addition to the presence of gamma radiations causing additive noises.

In order to evaluate the performance of the proposed approach when applied to neutron radiography images, we make use of corrupted images taken by neutron radiography in a hostile site. Computer simulations prove that BFO Algorithm yields excellent results and presents good efficiency and can contend other methods, Fig.6.

Conclusions

In this paper, we have introduced E.Coli Bacteria Foraging Optimization (BFO) algorithm for image enhancement to solve the ill-posed minimization problem based on minimizing the total variation. The Laplacian constraint has been used for regularization to smooth deblurred images in presence of noise. In our experiment, we have tested this algorithm on benchmark gray level test images, and then we apply it for neutron radiography images. The method always converges to good results, from quality point of view, with computation time proportional to matrix (image) size compared to iterative algorithms that need much processing time. Different types of blurs and noises are tested with optimal weight λ chosen based on many trials and readings of PSNR progress. Compared to some state of the art methods, this approach reveals optimistic result and promising efficacy. Application to neutron radiography images taken using imaging system put in a hostile medium gives acceptable results and more improvements are left for future studies. We intend to extend its feasibility for other types of image processing applications and examine hybridization of swarm Algorithms in order to improve convergence and achieve better results.

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***Authors**: Slami SAADI, PhD student, Department of electronics, university saad Dahlab of Blida, Algeria,E-mail: saadisdz@yahoo.fr; prof.Abderrezak GUESSOUM, Department of electronics, university saad Dahlab of Blida, Algeria, E-mail: guessouma@hotmail.fr ; prof. Maamar BETTAYEB, Department of Electrical and Computer Engineering Sharjah university, UAE.E-mail: maamar@sharjah.ac.ae.*