Deconvolution of Neutron Degraded Images: Comparative Study between TSVD, Tikhonov Regularization and Particle Swarm Optimization Algorithm

Slami Saadi, Maamar Bettayeb, *Senior Member, IEEE,* and Abderrezak Guessoum, *Member, IEEE*

***Abstract*—Image deconvolution is an important problem in image processing. It is an ill-posed inverse problem, so regularization techniques are used to solve this problem by adding constraints to the objective function. Various popular algorithms have been developed to solve such problem. This paper proposes a new approach to the nonlinear neutron degraded images restoration problem which is useful in many images enhancement applications, based on swarm intelligence. We use the particle swarm optimization (PSO) applied for total variation (TV) minimization, instead of the standard Tikhonov regularization method. In this work, we attempt to reconstruct or recover neutron radiography images that have been degraded during acquisition; using some a priori knowledge of the degradation phenomenon. The truncated singular value decomposition (TSVD) method is also considered for image deconvolution in this paper. A comparison between the five methods is conducted, using several images.**

***Index Terms*—Deconvolution, ill-posed, TV, Tikhonov, TSVD, PSO, regularization**

I. Introduction

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 can not 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].

We can broadly classify restoration techniques into two classes: the filtering reconstruction techniques and the algebraic techniques. The filtering techniques are rather classical and they 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.

Manuscript received October 25, 2009. Revised December 25, 2009

S. Saadi is with the Department of Instrumentation, Nuclear Research Center of Birine (CRNB), BP180, Ain-Oussera 17200, Algeria. Phone: +213772817158, e-mail: saadisdz@yahoo.fr .

M. Bettayeb is with the Electrical & Computer Engineering Department, College Of Engineering, University Of Sharjah, P.O.Box 27272, Sharjah, United Arab Emirates, (e-mail: maamar@sharjah.ac.ae) .

A. Guessoum is the head of Signal and Image Processing Laboratory (LATSI), Electronics Department, Blida University, LATSI Laboratory, B.P. 270 Blida Algeria, (e-mail: guessouma@hotmail.com).

By selecting the proper filter, one can get a good estimate of the original image signal, by reducing the effect of noise. 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. A limitation in this filter is that it cannot handle dynamically changing image and noise signals. 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.

The ill-posedness of this problem arises from the fact that the kernel of the blurring function is badly conditioned and the degraded image contains noise. As a result, small perturbations in additive noise may lead to significant oscillations in the inversion result when using matrix inversion solution. Therefore, to correctly recover the unknown original image, regularization is necessary. We can use regularization in frequency domain but this can result in unlimited amplification of noise. The main shortcoming of the frequency domain regularization methods is the difficulty of finding the appropriate ending frequency at which the blurring function will vanish quickly [2].

Spatial domain regularization methods are a wide research field for image restoration problems. In the spatial domain, the canonical regularization method is the Tikhonov regularization. The basic regularization theory was first proposed by Tikhonov and Arsenin [3].

The solution methods for this optimization problem include singular value decomposition (SVD) based direct method [3], Newton and quasi-Newton method [4], gradient methods (e.g. steepest descent (SD) method and conjugate gradient (CG) method) and various preconditioning techniques. CG method has proven to be an efficient iterative regularization method for recovering the correct image from its degradation [5]. This method overcomes the difficulty of choosing the regularization parameter by controlling the iteration indices but, the optimal stopping iteration index still depends on the noise level.

Total variation (TV) is a regularization approach that performs edge preserving image restoration, but at a high computational cost. Total variation regularization requires linearization of a highly nonlinear penalty term, which increases the restoration time considerably for large scale images. In the total variation method, we will consider an iterative regularization approach in the spatial domain, which was first addressed in optimization as the Barzilai-Borwein minimization (BB) method [6]. Iterative techniques have a common problem: the error starts increasing after it reaches a minimum. The first few iterations restore the low frequency components of the signal and, as the number of iterations increases, the algorithm attempts to restore the high frequency components, which are dominated by noise. Solution to such problem can be attained by adding a median filter to maintain a low error by preserving the edge information while reducing the high frequency error [7].

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. The novel approach introduced in this paper is to take advantage of particles swarm intelligence in order to facilitate the optimization process in total variation regularized methods. For our test images, we consider the physical meaning of the widely used 8-bit images; the pixel value varies from 0 to 255. We then reformulate the optimization problem by imposing the nonnegative constraints.

II. Deconvolution Using a General Linear Model

We model the blurring of images as a linear process characterized by a blurring matrix H of dimensions NxN, with $N=mxn$ and an observed image g which, in vector form, are related by the equation:

$$Hf = g \tag{1}$$

Where f is the original image

The reason $H^{-1}g$ cannot be used to deblur images is the amplification of high-frequency components of the noise in the data, caused by the inversion of very small singular values of H. Practical methods for image deblurring need to avoid this pitfall [1]. Obtaining f from Equation (1) is not a straight forward task since, in most cases of interest, the matrix H is ill-posed. Mathematically this means that certain eigenvalues of this matrix are close to zero, which makes the inversion process very unstable. For practical purposes, this implies that the inverse or the pseudo-inverse solutions: $f_1=H^{-1}g$ and $f_2= (H^T H)^{-1} H^T g$ amplify the noise and provide incorrect results. This means that image signals die out faster than noise signals in high frequencies.

III. Singular Value Decomposition

Singular value decomposition (SVD) is one of the most successful tools in the theory of inverse problems. It can be used to understand the ill-posed inverse problem and for describing the effect of the regularization method. It has been widely applied in image processing. In numerical analysis, the SVD provides a measure of the effective rank of a given matrix. In statistics and time series analysis, the SVD is particularly a useful tool for finding least-squares solutions and approximations.

Singular value decomposition has been successfully applied to many image restoration problems. Usual applications include linear space invariant and linear space variant pseudoinverse filtering, image enhancement, separation of 2-D filtering operations into 1-D filtering operations, generation of small convolution kernels, etc... Among all unitary transformations, SVD is optimal for a given image in the sense that the energy packed in a given number of transformation coefficients is maximized. Although applicable in many image restoration applications, SVD is severely limited because of a large number of computations required for calculating singular values and singular vectors of large image matrices.

The SVD of an mxn matrix A is given by:

$$A=U\sum V^T \tag{2}$$

Where $U=(u_1, u_2,..,u_n)\in R^{mxm}$ and $V=(v_1, v_2,.. v_n)\in R^{nxn}$ are two column-orthogonal matrices. Σ is a diagonal matrix with entries $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_N \geq 0$. For a blurring matrix, all the singular values decay gradually to zero and the condition number $cond(A) = \sigma_1 / \sigma_N$ is very large. We use the SVD approach to damp the effects caused by ……….. One approach to damp the effects caused by division of small singular values is to simply discard all SVD components that are dominated by noise, typically the ones above a certain truncation parameter. The resulting method is, for obvious reasons, referred to as the truncated SVD, or TSVD method [1].

IV. 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 [8].

The Tikhonov regularized minimum norm solution of the equation: $g = Hf + \eta$ is the vector $F_\delta \in \Re^N$ that minimizes the expression :

$$\left\|Hf - g\right\|_2^2 + \lambda^2\left\|Lf\right\|_2^2 \tag{3}$$

where $\lambda > 0$ is called a regularization parameter

We denote:

$$F_\delta = \arg\min_f \left\{\left\|Hf - g\right\|_2^2 + \lambda^2\left\|Lf\right\|_2^2 \right\} \tag{4}$$

Regularization can be understood as a balance between two requirements:

1. f should give a small residual Hf-g.
2. f should be small in L^2 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 (4) .

V. Total Variation Regularization

Total variation (TV) is often used for image filtering and restoration. TV based filtering was introduced by Rudin, Osher, and Fatemi [9]. It is an effective filtering method for recovering piecewise-constant signals. Many algorithms have been proposed to implement total variation filtering. The most famous one used in this comparison is by Chambolle [10]. The derivation in this algorithm is based on the min-max property and the majorization-minimization procedure. Rudin, Osher and Fatemi introduced in 1992 the following idea:

Instead of minimizing: $\left\|Hf - g\right\|_2^2 + \lambda\left\|Lf\right\|_2^2$ (5)

They minimized: $\left\|Hf - g\right\|_2^2 + \lambda\left\|Lf\right\|_1$ (6)

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

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

The idea is that (6) should allow occasional larger jumps in the reconstruction leading to piecewise smoothness instead of overall smoothness. It turns out that (6) is a justified objective function, but the minimization is more computationally involved.

VI. Particle Swarm Optimization

The particle swarm optimization algorithm was first described in 1995 by James Kennedy and Russell C. Eberhart [11]. The technique has evolved greatly since then. Particle swarm optimization is a stochastic, population-based evolutionary computer algorithm for problem solving. In a PSO system, a swarm of individuals (called particles) fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of a particle is influenced by the best position visited by itself (i.e. its own experience) and the position of the best particle in its neighborhood (i.e., the experience of neighboring particles). When the neighborhood of a particle is the entire swarm, the best position in the neighborhood is referred to as the global best particle, and the resulting algorithm is referred to a global best PSO. When smaller neighborhoods are used, the algorithm is generally referred to a local best PSO. The performance of each particle (i.e. how close the particle is from the global optimum) is measured using a fitness function that varies depending on the optimization problem.

Each particle in the swarm is represented by the following characteristics:

x_i : The current position of the particle;

v_i : The current velocity of the particle;

y_i : The personal best position of the particle.

$\hat{y}$: The neighborhood best position of the particle.

The personal best position of particle i is the best position (i.e. the one resulting in the best fitness value) visited by particle i so far. Let F denote the objective function. Then the personal best of a particle at time step t is updated as:

$$y_i(t+1) = \begin{cases} y_i(t) & if\ F(x_i(t+1)) \geq F(y_i(t)) \\ x_i(t+1) & if\ F(x_i(t+1)) \prec F(y_i(t)) \end{cases} \tag{7}$$

For the $gbest$ model, the best particle is determined from the entire swarm by selecting the best personal position. If the position of the global best particle is denoted by the vector $\hat{y}$, then:

$$\hat{y} = \in \{y_0, y_1, y_2, \ldots. y_{s-1}, y_s\} \tag{8}$$

Where:

$$\hat{y} = \min\{F(y_0(t))\ldots, F(y(t))\} \tag{9}$$

And: s denotes the size of the swarm.

The velocity update step is specified for each dimension j : $j \in \{1, \ldots\ldots N_d\}$

Hence, $v_{i,j}$ represents the j^{th} element of the velocity vector of the i^{th} particle. Thus the velocity of particle i is updated using the following equation:

$$v_{i,j} = \omega \cdot v_{i,j}(t) + C_1 \cdot \Delta_1 + C_2 \cdot \Delta_2 \tag{10}$$

Where:

$$\Delta_1 = r_{1,j} \cdot (y_{i,j}(t) - x_{i,j}(t)) \tag{11}$$

$$\Delta_2 = r_{2,j} \cdot (y^n{}_j(t) - x_{i,j}(t)) \tag{12}$$

ω is the inertia weight, C_1 and C_2 are the acceleration constants, and $r_{1,j}$, $r_{2,j}$ are random coefficients distributed as: $r_{1,j}\ and\ r_{2,j} \in [0,1]$ (13)

The position of particle i, x_i is then updated using the following equation:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{14}$$

This process is repeated until a specified number of iterations is exceeded, or velocity updates are close to zero. The quality of particles is measured using a fitness function which reflects the optimality of a particular solution. The following steps summarize the basic PSO algorithm [11,12]:

<u>Algorithm:</u>

For each particle i =1,...,s do
 Randomly initialize xi
 Randomly initialize vi (or just set vi to zero)
 Set yi = xi
endfor
Repeat
For each particle i = 1,...,s do
 Evaluate the fitness of particle i, f(xi)
  Update yi using equation (7)
  Update $\hat{y}$ *using equation (9)*
 For each dimension j = 1,...,Nd do
 Apply velocity update using equation (10)
 endloop
 Apply position update using equation (14)
endloop
 Until some convergence criteria is satisfied

It is important to clarify that a good choice of the initial population can make the PSO converges to the global minimum. For this reason the work in [13] used the normal cloud method to find the best initial population. In this paper, for the presented case, the choice of the initial population is made by a simple instruction:

$$x_{i,j}(0) = \frac{\pi}{2k} \cdot (j - 1 + rand)$$

Where *k* is the dimension of the objective function.

VII. Simulation Results

The benchmark image used for comparison is created using the *checkerboard* MATLAB function. The original image is hardly blurred using the motion blur function, Fig.1:

$$h(i)=\begin{cases}\frac{1}{L}, if -\frac{L}{2}\leq i\leq\frac{L}{2}\\ 0, otherwise\end{cases} \quad (15)$$

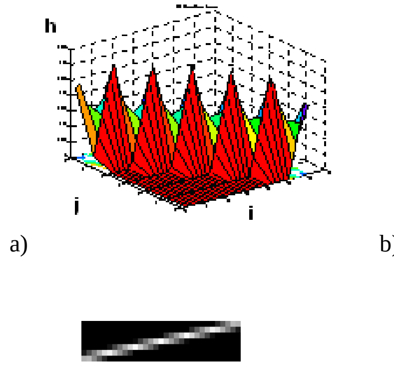

Fig.1: The 2-D Motion Blur Function, a)plotting the PSF in two dimensions h(i,j), b)showing the blur image

In our application we consider a common additive noise model that comes essentially from the following three sources:

- Photoelectric noise of background photons, from gamma sources. This kind of noise is typically modelled by a Poisson process.
- Noise from electronics used to capture images, modelled usually by a white Gaussian noise, with zero mean and a fixed standard deviation proportional to the amplitude of the noise.
- Film grain noise, from the randomness of silver halid grains in the film used for recording.
- Quantization noise which occurs during image digitization.

In Fig.2, we present the restoration of a *checkerboard* image that has been blurred and with added noise using a motion function, Fig.2.b. Three methods of restoration: inversion filter, zero padding in frequency domain and truncated singular value decomposition (Fig.2.c, d and e). In the TSVD, the condition number *cond(A)* = σ_1 / σ_N was found to be 7.337638 x 10^4.

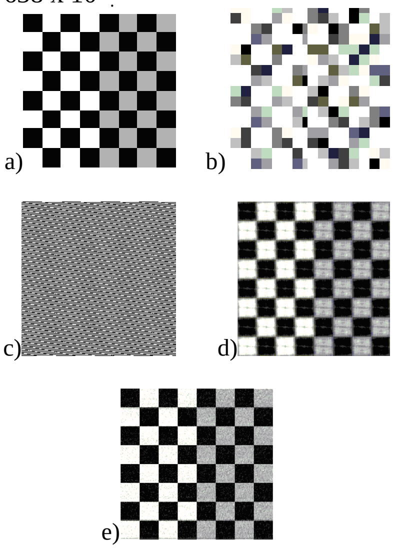

Fig.2:a)Original Image, b)Blurred and Noisy Image, c)Restored with Inverse Filter, d)With FFT and zero padding, e)With Truncated Singular Value Decomposition (TSVD)

A. *Total Variation Minimization with Regularization*

An implementation of the Total Variation based filtering introduced by Rudin, Osher, and Fatemi [9], was done using the conjugate gradient method and the Newton Algorithm for minimizing Total Variations with Laplacian regularization. Fig.3 shows restorations both with Tikhonov regularization (Fig.3a) and with R.O.F (Fig.3b) and also shows TV energy evolution with iterations (Fig.3c):

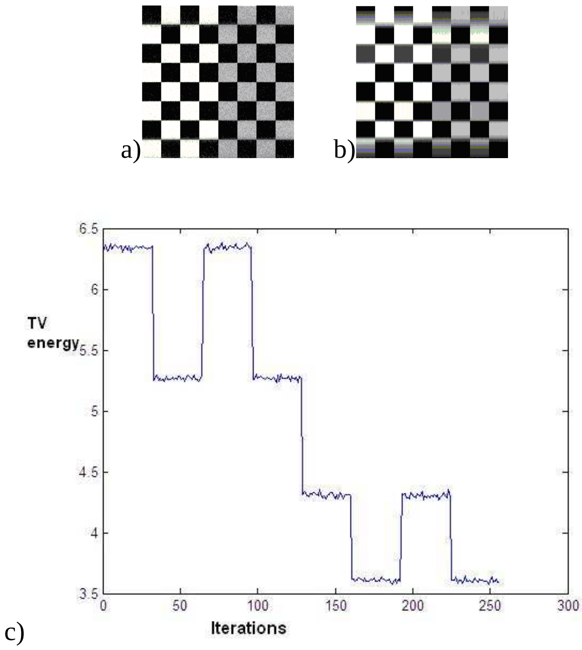

Fig.3: a)Restoration with Tikhonov Regularization, b)With (Rudin, Osher and Fatemi) method, c)TV Energy evolution with iterations

B. *Minimization using Chambole Algorithm*

Antonin Chambolle describes in [10] an iterative algorithm for the resolution of the TV regularized restoration problem (the so called "Rudin-Osher-Fatemi" method). This algorithm exploits a dual formulation of the minimization problem, and uses a fixed point iteration to find a solution of the dual formulation. Chambolle proves that these iterations are contractant, and thus converge to a solution with linear speed. Chambolle also exposes some important extensions of this algorithm such as the regularization parameter *lambda* that can be updated during the iterations in order to solve the L^2 constrained problem (instead of *Lagrangian* regularization). This is very useful if one knows the level of noise that is perturbs the measurements. Fig.4 illustrates a restoration result of the previous blurred/noisy image (Fig.4a) with estimation of regularization parameter and TV energy evolution with iterations (Fig.4b).

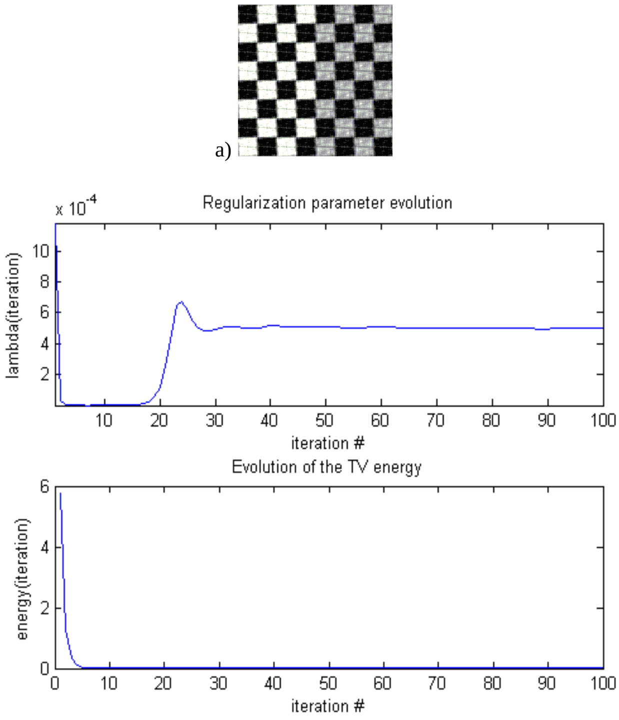

Fig.4: a)Image Restored using Chambolle Algorithm, b)Regularization parameter and TV energy evolution

C. *TV minimization Using PSO*

In this section, we introduce a new approach to solve a constrained optimization ill-posed problem in order to improve a blurred or noisy neutron radiography image. We convolve many types of degradation functions with images of different sizes, and then attempt to restore the original image. Our starting image is a grey level image contained in the *mxn* matrix. Each element in the matrix represents a pixel's grey intensity between black and white (0 and 255).

Assume we know how fast the blurring function operator is known. The simplest approach is to solve the problem in a sense of least square error between the estimated and the true image under the requirement of preserving the image smoothness:

$$\min(\|h * X - g\|_2) \qquad (16)$$

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, a regularization term is added to improve smoothness of the estimate:

$$0.004 * \|L * X\|_2 \qquad (17)$$

Where || || is the spectral norm and *L* is the discrete Laplacian, which relates each pixel to those surrounding it. *L = del2(X)* is a discrete approximation of:

$$L = \frac{\nabla^2 X}{2N} = \frac{1}{2N}\left(\frac{d^2 X}{dx^2} + \frac{d^2 X}{dy^2}\right) \qquad (18)$$

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 that 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 a deblurred image, we want to solve for *X*:

$$min(\|h*X - g\|_2 + 0.004*\|L*X\|_2) \qquad (19)$$

We can implement our objective function using this expression; the number of variables in this objective function to be minimized will be *mxn* which is the size of the matrix representing the original image.

We carried out computer simulations to validate the applicability of this algorithm in image restoration. We run the algorithm using Intel Pentium4 PC with 1.80GHZ CPU and memory size of 1Go. The average processing time is dependent upon computation machine, image size and choice of PSO algorithm parameters (varies from few seconds to few minutes). Some simple images of sizes: 8x8, 16x16, 24x24 and 32x32 created by the MATLAB function *checkerboard* are used. Different PSO parameters are choosen: C1 = 1.5; C2 = 4 - C1; minInertia = 0.3; maxInertia = 0.95; Swarm Size = 10,20,50,120; Maximum Iterations = 20,50,100,200. We took the value 0.004 as a regularization parameter. In Fig.5(a, b, c and d), we increase gradually the swarm size and iterations to reach improved restoration results. The cost function minimization is traced in Fig.6a without regularization and in Fig.6b with regularization.

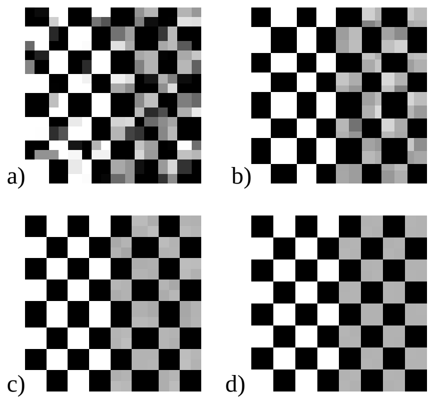

Fig.5: Restoration of Blurred and Noisy Images with Regularization Constraint and four different swarm sizes and iterations: a)10,20,b)20,50,c)50,100, and d)120,200

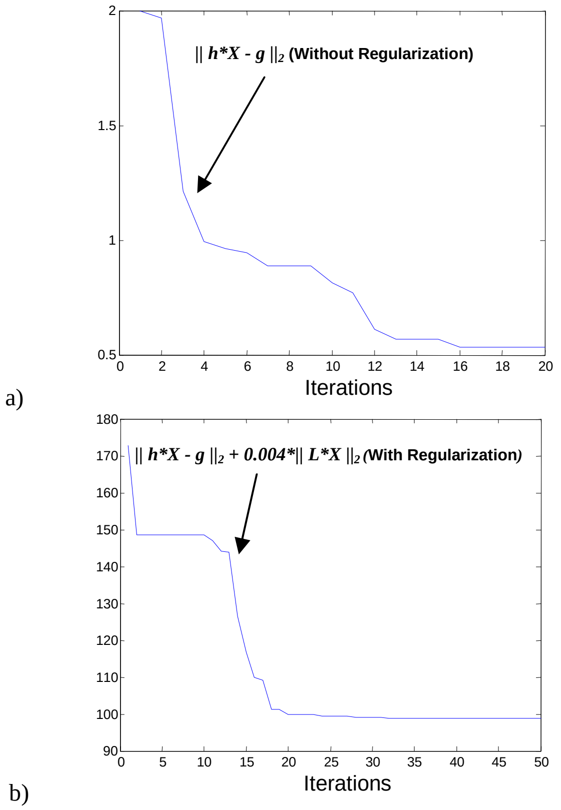

Fig.6: Evolution of Cost function: a)Without regularization, b)With regularization,

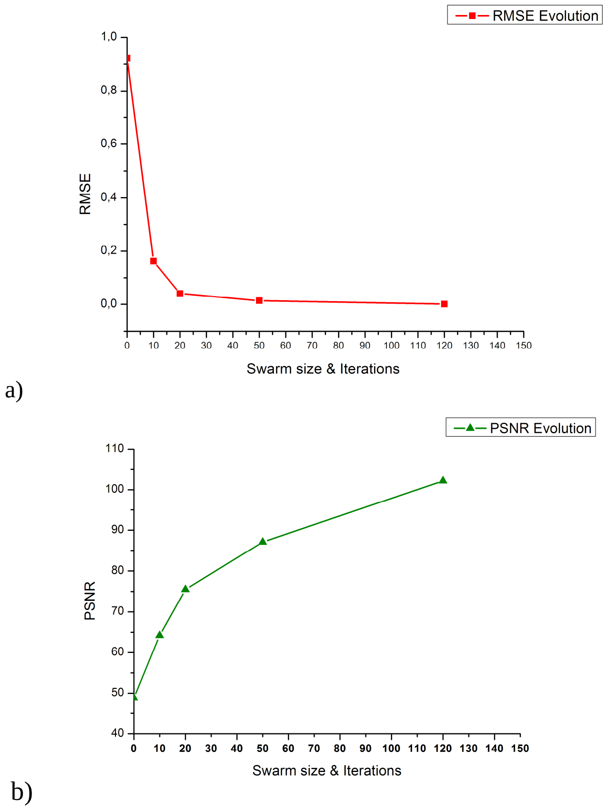

Fig.7: Evolution of: a) RMSE, b) PSNR With Swarm Size & Number of Iterations

To evaluate the restoration performance of our approach quantitatively, we record the evolution of the root mean squared error (RMSE) and the peak signal to noise ration (PSNR) in Table1 and Fig.7.a, b:

$$MSE = \frac{1}{mxn}\sum_{i=1}^{i=m}\sum_{j=1}^{j=n}\left[original(i,j) - restored(i,j)\right]^2$$

and $RMSE = \sqrt{MSE}$

$$PSNR = 20.\log_{10}\left(\frac{255}{RMSE}\right)$$

Table1: Evolution of the (RMSE) and the peak signal to noise ratio (PSNR) with swarm size and number of iterations

	RMSE	*PSNR*
Blured/Noisy	0.921	48.81
(10,20)	0.162	64.21
(20,50)	0.041	75.49
(50,100)	0.014	87.06
(120,200)	0.001	102.17

Table2: Values of the RMSE) and the PSNR for five different known methods

	RMSE	*PSNR*
Blured/Noisy	0.921	48.81
FFT	0.1680	64.01
TSVD	0.0795	70.47
Tikhonov	0.0682	71.47
TV (CG)	0.2124	61.53
TV (Chambolle)	0.1401	65.26

In our experiment, the proposed particle swarm method always converges to acceptable results, from a quality point of view, with the computation time proportional to the matrix (image) size. Different types of blurring and noises are tested with the optimal regularization parameter λ chosen based on many trials and PSNR progress. In Table2, we applied five methods to restore the test image; numerical results show that these methods are promising for large-scale image restoration problems. We remark also that using TSVD as a direct method; the computed restorations are comparable to iterative methods but are computationally less expensive. Though in particle swarm intelligence method, we can obtain a closer approximation of the true image with very good RMSE and PSNR (0.001 and 102.17) compared to the other five methods; the number of iterations is a little larger and requires long computation time which merits further research, and regularization deserves a rigorous study to attain better results.

D. *Application to Neutron Images:*

The digital neutron image is acquired by a certain radiological procedure such as neutron radiography system, Fig.8, installed around a nuclear reactor. It is a two-dimensional *mxn* array of non-negative integers (gray levels). For neutron radiography, the gray level value represents the relative linear neutron attenuation coefficient of the object [14]. In the following, we present some experiment results that we try to restore using the new approach based on the PSO algorithm, Fig.9. the blurring is due to the neutron beam distribution from channel and we consider a common additive noise that comes essentially from gamma sources, electronics used to capture images, and from grains in the film used for recording. There are many varying parameters (swarm size and number of iterations) on which the quality of restorations depends.

Although it is very difficult and almost impossible to determine the best set of these parameters, it is very important that a reasonably effective set of these parameters is chosen, so that the deblurred image quality is accepted enough for use.

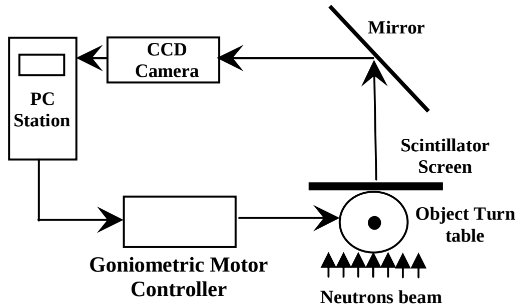

Fig.8: Neutron Radiography System [14]

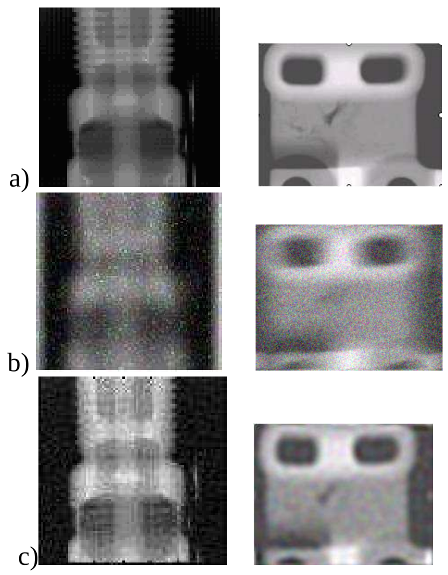

Fig.9: Neutron Radiography Images Restoration (Regularized) with swarm size and iterations (120,200): a)Original, b)Blurred/Noisy, c)Restored

VIII. Conclusion

In this work, we investigated the performance of an enhancement method for neutron radiography images blurred and with noise added during acquisition. The new approach introduced in this paper is the PSO algorithm with normal cloud mutation to solve the ill-posed minimization problem. The Laplacian constraint has been used for regularization to smooth the deblurred images in the presence of unknown type of noise. Computer simulations and visual inspection of produced images illustrate that the PSO algorithm yields optimistic results and good efficiency in restoration of images degraded by noise with comparison to other classical techniques. To achieve better results in visual quality, further efforts are requested.

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Mr. S.Saadi, Born in Algeria, 1969. Received his BSc degree in Electrical and Electronics Engineering from INELEC(1993), University of Boumerdes (Algeria) and MSc degree in Signal Processing from the University of Blida (2005). He is currently working towards a Ph.D Degree both at the University of Blida (Ageria) and University of Sharjah (UAE). His interests includes Artificial Intelligence applied to Signal and Image Processing, hardware and software reconfigurable implementation of digital signal processing tools, embedded electronics…etc.

He worked as an engineer in industrial instrumentation for more than ten years in the Algerian power systems society. He is, currently, with the national nuclear research centre of Birine (CRNB) as an associate researcher and lecturer in Signal Processing and Computer Science at Zian Achour University of Djelfa, Algeria.

Mr.Saadi has published many journal and conference articles and technical reports, proposed solutions to many instrumentation problems and has participated in the implementation of many systems such as neutron radiography and tomography imaging system.

Prof. M.BETTAYEB, received his BSc (1976), MSc (1978) and PhD (1981) degrees in Electrical Engineering from University of Southern California, Los Angeles, California, USA. He is currently a Prof. at Sharjah University, UAE and Coordinator, of Intelligent Systems Research Group. He is also Editor-in Chief of UOS Journal of Pure & Applied Sciences and senior Member, IEEE and a Member in the International Federation of Automatic Control (IFAC). His interests are Large Scale Systems Analysis and Design, $H\infty$ Control and Filtering, Identification, Estimation & Filtering, Higher Order Statistics and Applications, Wavelets and Applications.

Prof. A.GUESSOUM, (S'78-M'84) graduated from the Ecole Nationale Polytechnique of Algiers in 1976. He received the MSc. and Ph.D. degrees from the Georgia Institute of Technology, Atlanta, in 1979 and 1984, respectively. He also received the MSc. degree in applied mathematics from Georgia Tech in 1983. During the academic year 1984-1985 he was an Assistant Professor of Computer Science at Jackson State University, Jackson, MS. Currently he is teaching signal processing at the University of Blida (Algeria) and leading the Laboratory of Signal and Image processing (LATSI) at Blida University. His interests include signal/Speech processing, intelligent Computing, embedded electronics.