A NEW BI-PHASED IMAGE RESTORATION

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ABSTRACT

In This work a new method for image restoration is proposed. This new method is constituted of two phases. The first phase which is initialization phase, from a blurred image we get a new one by the use of the search efficiency function based on Levy distribution as first cost function. In The second phase, the obtained image is introduced to PSO for local restoration where a restoration cost function is used. The results obtained were excellent.

KEYWORDS: Image restoration, PSO, Lévy distribution, search efficiency function

1 INTRODUCTION

Image restoration is the operation of recovering the image from its degraded version. It is classified as a pre-processing step. In This work we deal with the restoration of blurred images, and in most of cases these blurred images are also degraded by an additive noise. The restoration principle of a degraded image is as follows (**figure.1**):

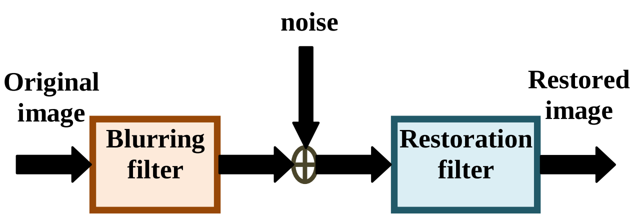

Figure 1: Principle of image restoration

The degraded image is formulated by equation (1) as follows:

$$g(x,y) = h(x,y) * f(x,y) + n(x,y) \qquad (1)$$

Where h: represents the degradation, g, f and n represent respectively: degraded image, original image and additive noise.

Thus, the restored image is deduced by the following equation (2):

$$\hat{f}(x,y) = R(x,y) * g(x,y) \qquad (2)$$

Where R: represents the restoration filter, $\hat{f}$: the restored image and g: the degraded image.

In literature we found supervised restoration where the degradation is known. This operation is called simply restoration. And unsupervised restoration called blind restoration where lack of information about the degradation exists; this case is classified as ill- posed problem. Several techniques were used [1]- [5] and recent works [6]- [25] were carried out to lead to better results, and more effective techniques for both restoration types. We find global restoration techniques where the entire image is taken as an entity, and local restoration techniques that work by pixel. According to literature, most of the recently proposed techniques worked on probabilistic framework (Bayesian, Markov process, etc) [17]-[24], others use frequential transformations (FFT, DFT, DCT…, etc) [6, 7, 9, 15], or spatials (wavelet) [12], to execute multiscale restoration and others combine the both [18, 20, 23]. On the other hand, we find neuron networks, used alone or combined with other techniques [22, 24]. Also, in most of cases, the restoration is converted into an optimization problem to be able to exploit the maximum of good methods. Also, the Tikhonov regularization method has taken a large part of study and interest because of the big influence imposed by the regularization parameters on the restoration operation, and so on the obtained results [8, 16, 21]. Since this operation, which is restoration, is important in image processing process, the most important mathematical techniques have been exploited such as partial differential equations (PDE) [10]. The variety of applied techniques shows its importance and usefulness in several domains: spatial, medical, military … etc, and their goal is always to lead to better results than existing ones. Nevertheless, all those techniques suffer from heavy mathematical baggage implicated to carry out this task and more complex formulas developed. According to literature those techniques have given good results but suffer from complexities. That's why we have considered the application of the Particles Swarm Optimization technique (PSO) in this framework due to its simplicity and lightness and also because of the results that had been given in all domains where it was applied. But also this tool suffers from some problems as random initialization, so we have introduced a kind of initialization phase to resolve this problem.

Thus, the present paper is organized as follows: Particles Swarm Optimization technique is presented in section 2. Section 3 presents the Levy process. In section 4, the proposed restoration algorithm is presented. Our application results in section 5. And the conclusion is in section 6.

2 PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization is an evolutionary tool which uses "a population" of candidate solutions to develop an optimal solution of a problem. The degree of optimality is measured by a fitness function defined by the user [25- 28, 32]. This paradigm has emerged in 1995 in the United States. The PSO, which has roots in artificial life and social psychology as well as engineering and computer science, differs from evolutionary computation methods in that the population members called "particles" are scattered in the space of the problem [27] and [28]. The behaviour of the swarm is described from a particle view angle [28]- [31]. At first, the swarm is shared out in the search space; each particle has a random velocity. Then, at any time step, each particle is able to evaluate the quality of its position and keep in memory its best performance, y_i equation (3) , i.e. the best position it has reached until now and its quality. It is able to question a certain number of its own kind and get from each one of them its own best performance. It chooses the best of the best performances it knows, $\hat{y}_i$ equation (4), modifies its velocity according to this information and to its own data and it moves consequently, equations (5) and (6).

The search strategy of algorithms based on population as the PSO constitutes two phases, exploration and exploitation. The first is responsible for the detection of the more promising areas in the search space; the second permits to promote the convergence of the particles toward the best detected solution [31]. The PSO can be arranged under the class of iterative methods as well as within the stochastic techniques.

Each particle in the swarm is represented by the following characteristics [25-28]:

x_i : The current position of the particle *i.*

v_i : The current velocity of the particle *i*.

The update of the personal best position of a particle is as follows:

$$y_i(t+1)=\begin{cases} y_i(t) & si \quad f(x_i(t+1))\geq f(y_i(t)) \\ x_i(t+1) & si \quad f(x_i(t+1))< f(y_i(t)) \end{cases} \tag{3}$$

The position of the global best particle is then given by:

$$\hat{y}(t)\in\{y_0,y_1,\ldots y_s\}=\min\{f(y_0(t)),f(y_1(t)),\ldots f(y_s(t))\} \tag{4}$$

S: denotes the size of the swarm.

So the velocity of the particle *i* is updated using the following equation:

$$v_{ij}(t+1)=wv_{ij}(t)+r_1c_1\left(y_{i,j}(t)-x_{ij}(t)\right)+ r_2c_2\left(\hat{y}_j(t)-x_{ij}(t)\right) \tag{5}$$

Where: w is the inertia weight

c_1 and c_2 are acceleration constants

r_1 and r_2 are uniformly distributed variables.

j=1: D, where D: the dimension of the search space of the considered problem.

The position of the particle *i* is updated by the equation:

$$x_{ij}(t+1)=x_{ij}(t)+v_{ij}(t+1) \tag{6}$$

The equation (5) is the velocity vector which drives the search process and reflects the "sociability" of particles.

3 SEARCH EFFICIENCY FUNCTION

The scale free movement patterns of some individuals (independent foragers) have arisen a considerable interest because such patterns are known to constitute an optimal searching strategy when target sites are randomly and sparsely distributed. An idealised model in which a searcher moves on a straight line towards the nearest target if the target site lies within a direct vision distance, *r*, otherwise the searcher chooses a direction at random and a distance, *l*, drawn from a Lévy distribution, $P(l)\sim l^{-\mu}$ where $1< \mu <3$. It then moves incrementally towards the new location whilst constantly seeking for targets within a radius, *r*. If no target is sited, it stops after traversing the distance *l* and chooses a new direction and a new distance, otherwise it proceeds to the target. A Search Efficiency Function (SEF) $\eta(\mu)$ was defined by [34] to be reciprocal of the mean distance travelled by a searcher before detection of a target site:

$$\eta=\frac{1}{N_l\langle l\rangle} \tag{7}$$

Where $\langle l\rangle$ is the mean length of a flight- line segment and N_l is the mean number of straight- line segments traversed before arrival at a target site. The distance between successive targets is approximated by the mean distance between successive targets, λ,

$$\langle l\rangle=\left(\frac{\mu-1}{2-\mu}\right)\left(\frac{\lambda^{2-\mu}-r^{2-\mu}}{r^{1-\mu}}\right)+\frac{\lambda^{2-\mu}}{r^{1-\mu}} \tag{8}$$

This aspect of searching is captured by optimal Lévy-flights searching strategies. This is because such flights typically comprise of many, relatively short segments, punctuated by occasional longer segments. The search started from an arbitrary point, x_0 in the interval *[-λ/2, λ/2]*, the average number of straight- line flight- segments traversed before first reaching a target is

$$N_l = \frac{1}{2K}\left(\frac{(x_0 + L)(L - x_0)}{r^2}\right)^{(\mu-1)/2} \quad (9)$$

Where $L=\lambda/2$ and K is the diffusivity. The searching efficiency is dependent upon the initial location of the searcher.

4 PROPOSED METHOD

In previous work we have used the PSO, the powerful optimization tool, in image restoration problem [33]. It has given good results. But any evolutionary algorithm can suffer from the premature convergence, and it is essentially due to initialization which is generally random. To remedy this problem we propose the introduction of an initialization phase in image restoration procedure before the use of the PSO. Our proposed initialization is elaborated by the search efficiency function [34].

The proposed algorithm

i.Degraded image
ii.Phase 1: use of the SEF as cost function
iii.Phase 2: use of the CLSE as cost function
iv.Restored image

Phase 1: initial restoration phase

1. *L= taken as the maximum intensity of a pixel*
2. *x_0=degraded image*
3. *Calculation of N_l, from equation (9)*
4. *Calculation of $\langle l \rangle$, from equation (8)*
5. *Calculation of η, from equation (7)*
6. *Use of equation (3) for the best personal performance*
7. *Use of equation (4) for the best global performance*
8. *Use of equation (5) for the velocity update*
9. *Use of equation (6) for the position update*
10. *Get the first restored image*

Phase 2: final restoration phase

1. *Restored image from the phase 1*
2. *Use of equation (3) for the best personal performance*
3. *Use of equation (4) for the best global performance*
4. *Use of equation (5) for the velocity update*
5. *Use of equation (6) for the position update*

5 RESULTS DISCUSSION

To show the performance of this algorithm we used the cameraman image, figure 2. a, as a test. To evaluate the performances of our algorithm we have chosen the PSNR metric in **DB** [15]**.**

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (10)$$

Where, MSE is the Mean Square Error between the original image and the restored image.

The test image was degraded by a Gaussian blur (5x5) with variance $\sigma_f = 0.5$ mean $\mu_f = 0$. Firstly we restored the blurred image. Lastly we restored the blurred and noisy image. We used Gaussian noise with mean $\mu_n=0$, and variance $\sigma_n=0.002$. The degraded images are shown in Figure 2. b and c.

a

b

c

Figure 2: test images, a. original image, b. blurred image, c. blurred and noisy image

The algorithm has been implemented in Matlab7.8, Windows 7 on a calculator Intel (R) Core (TM)2 Duo CPU T6600 @2.20 GHz 2.20 GHz, 4 Go of RAM, 64bits exploitation system.

Test1. Concerns the restoration of blurred images Figure 3, Table 1 resumes the PSNRs of the results obtained.

Figure 3: restored image from a blurred one

Test2: Concerns the restoration of blurred and noisy images Figure 4, Table 1 resumes the PSNRs of the results obtained.

Figure 4: restored image from a blurred and noisy one

Table 1: PNSR results

Image	Degraded image	PSO	Proposed method
Blurred	31.0834	33.5485	35.3277
Blurred & noisy	28.3734	30. 8417	39.4372

The results obtained in two tests interpreted by figures 3 and 4 show the amelioration introduced by our method to the operation of image restoration, and to the PSO behavior. Table 1 proved its usefulness by PSNR metrics. The running time is estimated 9min compared with the time taken by the PSO in local restoration 5min [33]. Also the results show that our method performed well for blurred and noisy image, so we have obtained a robust tool, figure 4, the blurred and noisy image gave better PSNR compared to a blurred image, Table 1.

6 CONCLUSION

In previous work we have introduced the PSO in image restoration operation and we got good results. But the random initialization in this tool constituted its major drawback. So we have proposed the use of bi-phased restoration where the first phase is performed by the exploitation of the SEF defined by [34] as an optimal searching strategy of target sites performed by honeybees when searching for forage location. We got excellent results which can be ameliorated.

BIBLIOGRAPHIE

[1] Gonzalez R. C. & Woods R. E., *Digital Image Processing*, Second Edition, Prentice Hall, 2002.

[2] Mallat S., A Wavelet Tour Of Signal Processing, Second Edition, Academic Press, Elsevier (USA), 1999.

[3] Pratt W. K., *Digital Image Processing: PIKS Inside*, Third Edition, John Wiley & Sons, Inc., 2001.

[4] Perry S. W., Adaptive Image Restoration: Perceptron Based Neural Network Model and Algorithms, Ph.D. Theses, School of Electrical and Information Engineering University of Sidney, Australia, 1999.

[5] Smith S. K., *Digital Signal Processing*, A Practical Guide for Engineers and Scientists, Newnes, 2003.

[6] BI Xiao-jun, WANG Ting, “Adaptive Blind Image Restoration Algorithm of Degraded Image”, Congress on Image and Signal Processing, 2008 IEEE

[7] Feng-qing Qin, Jun Min, Hong-rong Guo, “A Blind Image Restoration Method Based on PSF Estimation”, World Congress on Software Engineering, 2009 IEEE

[8] Jianjun Zhang, Qin Wang, “A New Regularization Method for Bi-Level Image Restoration”, ICALIP2008, 2008 IEEE.

[9] Jinyoung Youn, Younguk Park, Jeongho Shin, and Joonki Paik, “Spatially Adaptive Image Restoration and Its FIR Implementation”, Second International Conference on Future Generation Communication and Networking Symposia, 2008 IEEE.

[10] Rajeev Srivastava, Harish Parthasarthyt, JRP Guptat and D. Roy Choudharyl, “Image Restoration from Motion Blurred Image using PDEs formalism”, IEEE International Advance Computing Conference (IACC 2009) Patiala, India, 6-7 March 2009.

[11] Satyadhyan Chickerur, Aswatha Kumar M , “A Robust Cluster Based Approach for Image Restoration”, IEEE Congress on Image and Signal Processing, 2008.

[12] Sun Jing, Wu Lehua, Gui Qi, “An Improved Multiscale Maximum Entropy Image Restoration Algorithm”, Proceedings of the First International Conference on Innovative Computing, Information and Control (ICICIC'06), IEEE, 2006.

[13] Sungjun Yim, Jeongho Shin, Joonki Paik, “Block-Based Fast Image Restoration”, Proceedings of the International Conference on Wavelet Analysis and Pattern Recognition, Beijing, China, 2007.

[14] Varlen Grabski, “Digital Image Restoration Based on Pixel Simultaneous Detection Probabilities”, IEEE Transactions On Nuclear Science, Vol. 56, No. 3, June 2009.

[15] Yoshinori Abe and Youji Iiguni, *“*Fast Computation Of The High Resolution Image Restoration By Using The Discrete Cosine Transform”, ICASSP, IEEE, 2007.

[16] Abd-Krim Seghouane, “Model Selection Criteria for Image Restoration”, IEEE Transactions On Neural Networks, Vol. 20, NO. 8, August 2009.

[17] J.K. Prasanna and A.N. Rajagopalan, “Image restoration using the particle filter: handling non-causality”, IEE Proc.-Vis. Image Signal Process., Vol. 153, No. 5, October, IEEE, 2006.

[18] Pradeepa D. Samarasinghe, Rodney A. Kennedy, Hongdong Li, “On Non-blind Image Restoration”, IEEE, 2009.

[19] S. Derin Babacan, Rafael Molina, and Aggelos K. Katsaggelos, “Parameter Estimation in TV Image Restoration Using Variational Distribution Approximation”, IEEE Transactions On Image Processing, Vol. 17, NO. 3, March 2008.

[20] Shuai Lou, Zhenliang Ding, Feng Yuan, Jing Li, “Image Restoration Based on Wavelet-Domain Contextual Hidden Markov Tree Model”, International Conference on Computer Science and Software Engineering, IEEE, 2008.

[21] Wang Hong-Zhi Zhao Shuang Lv Hong-Wu, “Super-Resolution Image Restoration with L-Curve”, IEEE Congress on Image and Signal Processing, 2008.

[22] Wen-Hao Lee, Shang-Hong Lai, and Chia-Lun Chen, *“*Iterative Blind Image Motion Deblurring Via Learning A No-Reference Image Quality Measure”, ICIP 2007.

[23] Xiaolei LU, Furong WANG, Hai HU, Benxiong HUANG, “Wavelet domain image restoration and parameters estimation based on variational Bayesian method and Student-t priors”, IEEE International Symposium on Computational Intelligence and Design, 2008.

[24] Youshen Xia, and Mohamed S. Kamel, *“*Novel Cooperative Neural Fusion Algorithms for Image Restoration and Image Fusion”, IEEE Transactions On Image Processing, Vol. 16, NO. 2, February 2007.

[25] Clerc M. and Kennedy J., “The Particle Swarm: Explosion, Stability and Convergence in a Multi- Dimensional complex Space”, IEEE Transactions on Evolutionary Computation, vol. 6, 2001.

[26] Dréo J. & Siarry P., *Métaheuristiques pour l’optimisation difficile*, Edition Eyrolles, 2003.

[27] Kennedy J. and Eberhart R. “Particle Swarm Optimization”, In Proceedings of IEEE International Conference on Neural Networks, Perth, Australia, vol. 4, 1995.

[28] Kennedy J. & Eberhart R.C., *Swarm Intelligence*, Morgan Kaufman Publishers, Academic Press, 2001.

[29] Omran M.G.H., Particle Swarm Optimization Methods for Pattern Recognition and Image Processing, PhD Thesis, University of Pretoria, November 2004.

[30] Van den Bergh F., *An Analysis of Particle Swarm Optimizers*, PhD Thesis, Department of Computer Science, University of Pretoria, South Africa, 2002.

[31] Vrahatis M.N., Parsopoulos K.E., “Parameter selection and adaptation in Unified Particle Swarm Optimization”, Mathematical and Computer Modelling, vol. 46, 2007.

[32] Wu, Q.H., Ji, T.Y. and Lu, Z., “A Particle Swarm Optimizer Applied to Soft Morphological Filters for Periodic Noise Reduction”, Evo Workshops, LNCS4448, 2007.

[33] A. Toumi, N. Rechid, A. Taleb-Ahmed, K. Benmahammed, “Particle Swarm Optimization forImage Deblurring”, 1st Mediterraniean Conference on Intelligent Systems and Automation, Annaba, Algeria, 2008.

[34] A.M. Reynolds,” Cooperative random Lévy flight searches and the flight patterns of honeybees", Physics Letters A 354, 2006.