An Improved Richardson-Lucy Algorithm Based on Genetic Approach for Satellite Image Restoration

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Abstract: *In the process of satellite imaging, the observed image is blurred by optical system and atmospheric effects and corrupted by additive noise. The deconvolution of blurred and noisy satellite images is an ill-posed inverse problem. In the literature, a number of image restoration methods have been proposed to reconstruct an approximated version of the original image from a degraded observation. The iterative method known as Richardson-Lucy deconvolution has demonstrated its effectiveness to compensate for these degradations. The efficiency of this method obviously depends on the iteration count that has a direct impact on the expected result. This decisive and virtually unknown parameter leads to the estimation of approximate values which may affect the quality of the restored image. In this paper, the idea consists of optimizing the iteration count of the Richardson-Lucy deconvolution by applying the genetic approach in order to get a better restoration of the degraded satellite image.*

Keywords: *Satellite image, spatially invariant blur, non-blind restoration, richardson-lucy deconvolution, genetic algorithm.*

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1. Introduction

The acquired satellite images subject the degradations which are due, on the one hand, to the intrinsic properties of instruments, and on the other hand, to the acquisition conditions. The field of digital image restoration began in the 1950s and early 1960s with the space program to compensate for these degradations in order to improve the quality of images [1, 13]. The objective of the restoration is to estimate from the degraded image an image as close as possible to the original image [4, 12]. When the blur linked to the image is spatially invariant i.e., stationary, the restoration amounts to performing the inverse operation which is the deconvolution. The impact of image restoration in various domains has spawned an entire arsenal of image restoration methods and approaches to remedy the effects of both blur and noise.

The treated method entitled Richardson-Lucy deconvolution has become popular in the field of astronomy. It is a non-blind image restoration method which requires a priori knowledge about the blur and the noise [6]. This iterative method has demonstrated reliability with respect to the improvement of the image quality that actually depends on the iteration count, which is the crucial factor on which the quality of the image is based. This virtually unknown parameter leads to the estimation of approximate values which may reduce the quality of the restored image. To avoid the static estimation of this parameter, the applying of genetic algorithm, which is an iterative algorithm of optimum research, remains an effective approach.

In this work, the idea revolves around the restoration of the satellite images degraded under the effect of spatially invariant blur and additive noise by applying the genetic approach to the Richadson-Lucy deconvolution method through the optimization of the iteration count of this method in order to achieve the optimal result.

The paper is organized as follows: in Section 2, we indicate some works proposed for the restoration of satellite images. In section 3, we present the fundamental concepts of the genetic algorithm. In section 4, we study the optimization of iteration count of the Richardson-Lucy deconvolution by genetic approach for satellite image restoration. In section 5, we evaluate the effectiveness of our idea by some experimental results. Finally, in section 6, we give a conclusion.

2. Related Works

Several methods and approaches of image restoration have been proposed in the literature. The inverse filter is simple to calculate and effective when the additive noise is absent, and when it is present, this type of filter amplifies the degradations and the resulting image is completely noisy [1]. The Wiener deconvolution processes the images degraded by both spatially invariant blur and additive noise, it attenuates the sensitivity of noise through the minimizing the mean square error between the original image and the estimated image [1, 7]. An amelioration has been brought to this method, which consists of iterating the Wiener filter to estimate the power spectral density of the original image that is rarely, if ever, accessible [7].

An overview of the blind image deconvolution through the problem formulation and existing approaches has been proposed in [3]. The paper [1] introduces the applications of digital image restoration, the sources of image degradation and some classical image restoration techniques. In [2], a new technique for the acceleration of iterative image restoration algorithms is proposed. The paper [16] presents a technique for image restoration by Richardson-Lucy algorithm where the optimized Point Spread Function (PSF) is generated by the use of genetic algorithm. The paper [5] proposes a new regularized Richardson-Lucy algorithm for remote sensing image deconvolution, a piecewise local regularization term is introduced to make the standard Richardson-Lucy algorithm capable of suppressing noise and ringing artifacts, and the proposed method is combined with residual deconvolution to strengthen the image edges. A blind deconvolution algorithm based on the Richardson-Lucy algorithm is presented in [6]. An improved Richardson-Lucy algorithm based on local prior is developed in [17]. Concerning the satellite imagery, a new approach has been proposed, in which a rough deconvolution is followed by noise filtering in the wavelet transform domain [8], the paper [9] presents a new practical deblurring method, Small-Support-Regularized (SSR) deconvolution, for low quality remotely sensed imagery, and the paper [18] proposes the satellite image deconvolution based on nonlocal means.

3. Genetic Algorithm

3.1. Basic Concepts

The genetic algorithms are based on the genetic evolution of species, schematically, they copy extremely simplified way certain behaviors of natural populations [10]. A genetic algorithm is part of the evolutionary algorithms. It is an iterative algorithm of optimum research based on a population of constant size composed of individuals named chromosomes. The constancy of the size of the population leads to a phenomenon of competition between chromosomes. Each of these latest represents the coding of a possible solution of the problem. The chromosome is formed of a set of elements called genes that may take several values belonging to an alphabet that is not supposed to be digital [11]. With each iteration, the resulting generation keeps the size of the previous population. The appearance of the new generation whose chromosomes are better suited to the environment as it is evaluated by the fitness function, improves the results by putting the focus on the principle of competition between chromosomes.

3.2. Genetic Operators

The passage from one generation to the next is done by applying the genetic operators. These operators are stochastic [10, 11, 14]. The genetic algorithm begins by the selection operator which consists of selecting the best chromosomes likely to give the optimal result, then comes the crossover operator that generates two new chromosomes (children) from two selected chromosomes (parents). This algorithm ends with the mutation operator by inversion of one or several genes of chromosome.

The Figure 1 shows the crossover operator that generates two new chromosomes from two selected chromosomes:

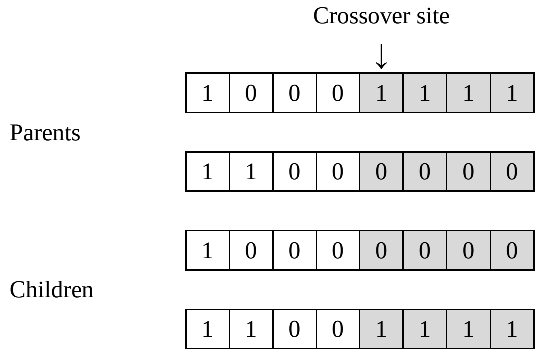


Figure 1. Crossover operator.

The Figure 2 illustrates the mutation operator by inversion of one gene of chromosome:

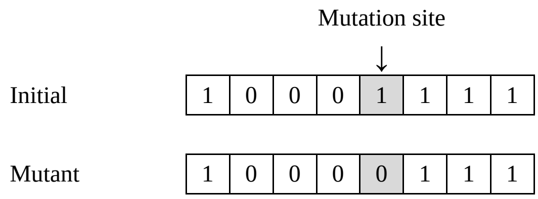


Figure 2. Mutation operator.

Generally, the crossover probability p_c is between 0 and 1, while the mutation probability p_m is between 0.001 and 0.01.

The different operations involved in a basic genetic algorithm are illustrated as follows [11]:

Algorithm 1: Standard genetic algorithm

Random generation of the initial population
Calculation of fitness function of each chromosome
Repeat
Selection
Crossover
Mutation
Calculation of fitness function of each chromosome
Until Satisfaction of the stop criterion

4. Proposed Work

4.1. Satellite Image Degradation

The acquired images by optical imaging systems are subject to degradation effects from out-of-control factors of blur and noise, leading to the lack of details and thus to the reduction of the image quality. The degradation can be caused in many ways, such as subject movement, out-of-focus lenses, or atmospheric turbulence [2, 4]. When the causes of blur are various and complicated, a Gaussian degradation model is used to approximate the composite effect [9]. The modelling of degradations suffered by the observed image is an essential step in order that the restoration takes place in good conditions. Indeed, the degradation process of a satellite image subjected to spatially invariant blur and additive noise is modelled by [4, 15, 18]:

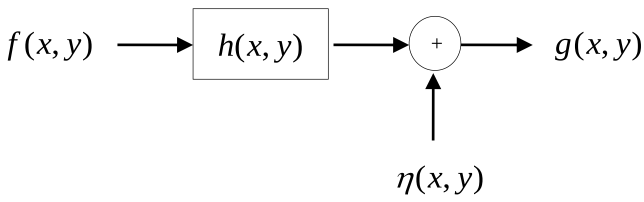


Figure 3. Image degradation model.

In the spatial domain, the modelling shown in Figure 3 is denoted as follows:

$$g(x,y) = f(x,y) * h(x,y) + \eta(x,y) \tag{1}$$

Where g represents the degraded image, * denotes the convolution operator, f is the original image, h is the degradation function which is also known as the Point Spread Function (PSF) and η is the Gaussian additive noise.

In the discrete domain, the Equation (1) can be expressed as:

$$g(x,y) = \sum_{m=-k}^{k} \sum_{n=-k}^{k} f(x-m, y-n) \times h(m,n) + \eta(x,y) \tag{2}$$

Where the size of mask h changes according to the parameters of blur.

4.2. Optimization of the Iteration Count of the Richardson-Lucy Deconvolution by Genetic Approach

The iterative image restoration algorithms are popular methods for deconvolving satellite images. These methods are nonlinear and offer more effective restoration than simple techniques such as linear inverse filtering. Nonlinear techniques are useful when the data is noisy or incomplete, which is usually the case in practical application of satellite image deconvolution [2]. The Richardson-Lucy deconvolution is an iterative method, allowing to estimate the solution $\hat{f}$ into a several iterations performed in the spatially domain. It attenuates the sensitivity of noise through the maximizing the likelihood of the observation $P(g|f)$:

$$\hat{f}^{k+1} = \hat{f}^{k} \cdot h^{*}\left(\frac{g}{h\left(\hat{f}^{k}\right)}\right) \tag{3}$$

Where k represents the iteration count and "." means the product of Hadamard (element by element).

It requires a lot of calculation, because it needs the application of a filter in an iterative manner. The restoration process can be monitored as it progresses by ending iteration that gives the acceptable result. This type of algorithm is the under influence of the iteration count. The estimation of the iteration count by genetic approach is a better asset to optimize this parameter. The application of the genetic algorithm to solve a problem needs to encode potential solutions to this problem in finite strings of bits to form the chromosomes, to find a selective function permitting a good discrimination between the chromosomes and to define the genetic operators which will be used. And thus, the genetic algorithm is applied to a population of constant size 5, whose each chromosome is encoded in a finite string of 8 bits in binary. The crossover probability p_c=0.6, while the mutation probability p_m= 0.005. And to have the expected result of this approach, it is essential to evaluate the chromosomes values through the fitness function which is the Signal-to-Noise Ratio (SNR) quality measure [18]:

$$SNR(f, \hat{f}) = 10\log_{10}\left(\frac{\|f\|_2^2}{\left\|\hat{f} - f\right\|_2^2}\right)(dB) \tag{4}$$

The selection phase uses the rank selection strategy to arrange the chromosomes in ascending order of their fitness value and to assign them a probability of selection according to their ranks, while the elitist strategy is adopted for the reproduction phase, which consists of keeping the best chromosome of the population during the transition from one generation to the next.

5. Experimental Results and Evaluations

5.1. First Experimentation

The test satellite image used in this work is a grayscale image of the toolbox "images" proposed by the MATLAB software.

In a first step, a study is performed on an image subjected to the degradation effects of the Gaussian blur (mask of 5×5, standard deviation σ_n =7), and the Gaussian additive noise (mean μ_n=0, variance σ^2_n=0.00001).

The execution of the genetic algorithm is rapid. The optimal chromosome is "00100011", which has the fitness value "22.03". The Figure 4 shows the evolution of the fitness value of the best chromosome in the current population depending on the generation:

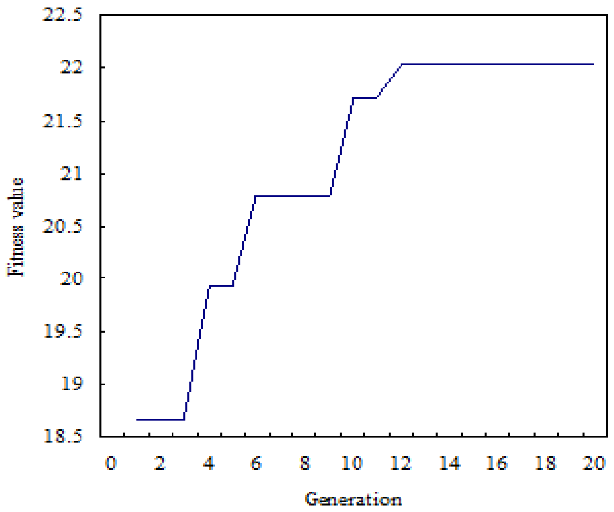
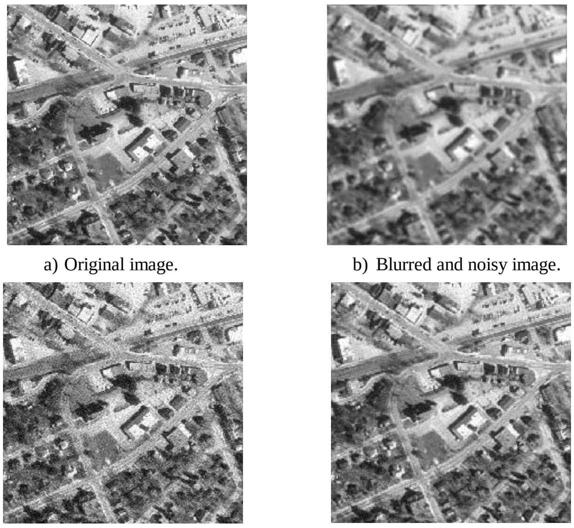


Figure 4. Evolution of the fitness value according to the generation.

The image quality is evaluated by the *SNR* quality measure. The Figure 5 shows the obtained result:



a) Original image.

b) Blurred and noisy image.

c) Richardson-Lucy deconvolution:*k*=130. *SNR*=17.19 *dB*,

d) Applying the genetic approach to the Richardson-Lucy deconvolution: *k*=35,*SNR*=22.03*dB*.

Figure 5. The result of the realized study.

In a second step, the study of the variation of *SNR* depending on σ_n and σ^2_n for the Richardson-Lucy deconvolution and its improvement by genetic approach, gave the results shown in Table 1:

Table 1. Variation of *SNR* depending on σ_n and σ_n^2 .

σ_n	σ_n^2	Richardson-Lucy deconvolution		Its improvement	
		k	*SNR*	*k*	*SNR*
1	0.001	10	17.76	6	19.63
2	0.0001	45	16.12	37	17.39
3	0.00001	12	24.93	43	25.26
4	0.0001	39	17.20	26	19.67
5	0.001	19	12.03	7	18.68

With the rise of *SNR*, the image quality improves, which is illustrated in Figure 5 and presented in Table 1, demonstrating that the amelioration of the Richardson-Lucy deconvolution method by genetic approach gives a better result and remains effective when the image is degraded by both Gaussian blur and Gaussian additive noise.

5.2. Second Experimentation

This time, a study is realized on an image degraded under the effects of the motion blur (length *L*=17, angle $\theta = 11^{\circ}$), and the Gaussian additive noise (mean μ_n=0, variance σ^2_n=0.00001).

The genetic algorithm converges rapidly. The optimal chromosome is "00101101", which has the fitness value "20.37". The Figure 6 shows the evolution of the fitness value of the best chromosome in the current population depending on the generation:

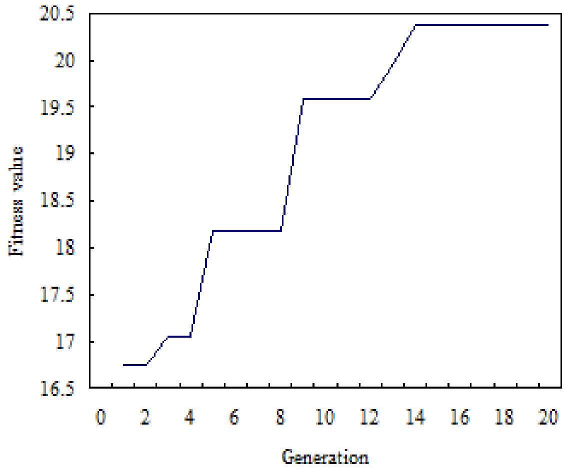
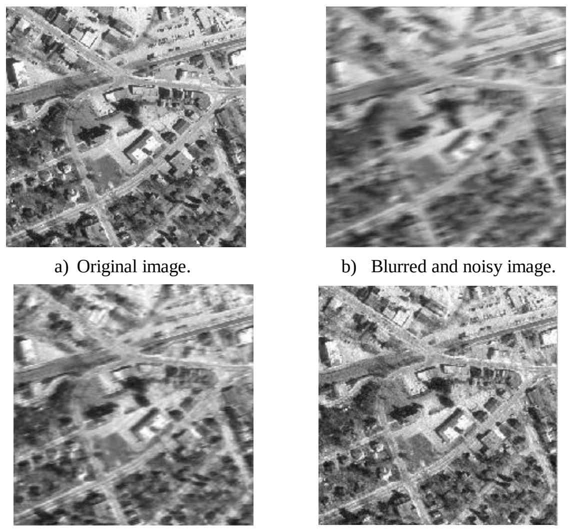


Figure 6. Evolution of the fitness value depending on the generation.

The same *SNR* quality measure is used to evaluate the image quality. The Figure 7 illustrates the result of the realized study:



a) Original image.

b) Blurred and noisy image.

c)Richardson-Lucy deconvolution: *k*=10, *SNR* =17.04 *dB*

d) Applying the genetic approach to the Richardson-Lucy deconvolution: *k*=45, *SNR* =20.37*dB*

Figure 7. The obtained result of the preformed study.

The Table 2 presents the results of the variation of *SNR* depending on *L*, θ and σ^2_n for the Richardson-

Lucy deconvolution and its improvement by genetic approach:

Table 2. Variation of *SNR* depending on L, θ and σ_n^2.

L	θ	σ_n^2	Richardson-Lucy deconvolution		Its improvement	
			k	***SNR***	***k***	***SNR***
10	45°	0.001	11	14.95	8	16.17
20	35°	0.0001	7	15.25	29	16.52
30	25°	0.00001	23	16.99	69	17.97
40	15°	0.0001	12	14.54	31	15.49
50	5°	0.001	6	12.19	17	13.03

When the image is degraded by both motion blur and Gaussian additive noise, the *SNR* corresponding to the proposed idea remains higher as shown in Figure 7 and summarized in Table 2, which illustrates the efficiency of the improvement of the Richardson-Lucy deconvolution method by genetic approach through the optimization of the iteration count.

6. Conclusions

The genetic algorithm rapidly converges towards the optimal solution. The applying the genetic approach to the Richardson-Lucy deconvolution for restoring the satellite image degraded by both spatially invariant blur and Gaussian additive noise affirms the compensation of the degradations and the improvement of image quality through the elevation of *SNR*, which demonstrates the effectiveness of the proposed work that is useful and valid as long as the satellite image to restore is weakly or moderately degraded.

The development of a new approach for the blind restoration when the blur in the degraded satellite image is spatially variant may be the subject of a study thereafter.

References

[1] Banham M. and Katsaggelos A., "Digital Image Restoration," *IEEE Signal Processing Magazine*, vol. 14, no. 2, pp. 24-41, 1997.

[2] Biggs D. and Andrews M., "Acceleration of Iterative Image Restoration Algorithms," *Applied Optics*, vol. 36, no. 8, pp. 1766-1775, 1997.

[3] Campisi P. and Egiazarian K., *Blind Image Deconvolution: Theory and Applications*, CRC Press, 2007.

[4] Dash R. and Majhi B., "Motion Blur Parameters Estimation for Image Restoration," *Optik-International Journal for Light and Electron optics*, vol. 125, no. 5, pp. 1634-1640, 2014.

[5] Dong W., Feng H., Xu Z., and Li Q., "A Piecewise Local Regularized Richardson-Lucy Algorithm for Remote Sensing Image deconvolution," *Optics and Laser Technology*, vol. 43, no. 5, pp. 926-933, 2011.

[6] Fish D., Walker J., Brinicombe A., and Pike E., "Blind Deconvolution by Means of the Richardson-Lucy Algorithm," *Journal of the Optical Society of America A*, vol. 12, no. 1, pp. 58-65, 1995.

[7] Hillery A. and Chin R., "Iterative Wiener Filters for Image Restoration," *IEEE Transactions on Signal Processing*, vol. 39, no. 8, pp. 1892-1899, 1991.

[8] Jalobeanu A., Blanc-Féraud L., and Zerubia J., "Satellite Image Deblurring Using Complex Wavelet Packets," *International Journal of Computer Vision*, vol. 51, no. 3, pp. 205-217, 2003.

[9] Li Y. and Clarke K., "Image Deblurring for Satellite Imagery using Small-Support-Regularized Deconvolution," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 85, pp. 148-155, 2013.

[10] Man K., Tang K., and Kwong S., *Genetic Algorithms: Concepts and Designs*, Springer Science and Business Media, 2012.

[11] Mitchell M., *An Introduction to Genetic Algorithms*, MIT Press, 1998.

[12] Moghaddam M. and Jamzad M., "Motion Blur Identification in Noisy Images using Mathematical Models and Statistical Measures," *Pattern Recognition*, vol. 40, no. 7, pp. 1946-1957, 2007.

[13] Molina R., Nunez J., Cortijo F. J., and Mateos J., "Image Restoration in Astronomy: A Bayesian Perspective," *IEEE Signal Processing Magazine*, vol. 18, no. 2, pp. 11-29, 2001.

[14] Poli R., Langdon W., and McPhee N., *A Field Guide to Genetic Programming*, Lulu Enterprises, 2008.

[15] Saadi S., Guessoum A., Bettayeb M., and Abdelhafidi M., "Blind Restoration of Radiological Images using Hybrid Swarm Optimized Model Implemented on FPGA," *The International Arab Journal of Information Technology*, vol. 11, no. 5, pp. 476-486, 2014.

[16] Shah M. and Dalal U., "3D-Image Restoration Technique using Genetic Algorithm to Solve Blurring Problems of Images," *The Imaging Science Journal*, vol. 62, no. 7, pp. 365-374, 2014.

[17] Yongpan W., Huajun F., Zhihai X., Chaoyue D., and Qi L., "An Improved Richardson-Lucy Algorithm based on Local Prior," *Optics and Laser Technology*, vol. 42, no. 5, pp. 845-849, 2010.

[18] Zhao M., Zhang W., Wang Z., and Hou Q., "Satellite Image Deconvolution Based on Nonlocal Means," *Applied Optics*, vol. 49, no. 32, pp. 6286-6294, 2010.

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