AN ENHANCED FRAMEWORK FOR SHARPENIG THE MULTISPECTRAL IMAGES USING GENETIC ALGORITHM

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Abstract: There are a number of applications in satellite remote sensing that require images with high spatial and reasonable spectral information. The fusion of the multispectral (MS) and panchromatic (pan) images or pan sharpening provides a high resolution (HR) colored image by merging the clear geometric features of the HR pan image and the color information of the MS bands. This HR pan image can be created by applying reconstruction techniques on the high-pass filtered bands of the MS image by utilizing the sub-pixel shifting between bands. In the proposed framework, the Genetic Algorithm (GA) is used for optimal estimation of the sub-pixel shifts between bands, blurring parameters for image reconstruction and adaptive weights for image fusion. The HR pan image is generated by GA-based Projections onto convex sets method. GA is considered global search methods. Therefore, it differs from those methods based on conventional high computation iterative solution of equations.Experimental results demonstrates an accurate sub-pixel image registration and animproved spatial quality of MS image by optimal estimation of the blur and the fusion weights for keeping a reasonable color appearance. Appropriate constraints improve the convergence rate of the GA-based registrationmorethan the classic methods.

Indexterms- Satellite image, Registration, Restoration, HPF Fusion, Sharpening, GA.

I. INTRODUCTION

The use of satellite imagery has widely increased with the developed onboard imaging systems. The spatial resolution of each satellite image depends on the sensor's physical characteristics such as its optics, its density of the detector elements and the spatial response of the detector elements [1]. Due to limitations in modifying the sensor or camera to improve resolution, and simply enlarging the image causes pixilation. Therefore, post-processing via image reconstruction is required to restore the degraded observed image and enhance the spatial resolution.Therefore, the received low resolution (LR) MSimages need to be processed to generate the HR image byregistration and reconstruction methods while keeping the noise in acceptable levels. This fact oriented the development of iterated image reconstruction techniques, in which the amount of image restoration can be controlled among the iterations of linear equation system solution with regularization or projection techniques and constrains on the solution. One of the most used projection technique is Projections Onto Convex Sets (POCS) [2]. The method of POCS was introduced by [3] in 1982. In [4], Stark explains the general technique for applying POCS in the field of image restoration. The concept of POCS applied to the problem of image reconstruction was introduced in [5]. The POCS method uses a priori information about the degradation or the imaging system. The key to effectively apply this kind of algorithm is to define the appropriate sets, compute the projection onto these sets, and incorporate the projectors into an image processing algorithm designed to meet some criteria implied by the constraints. Several techniques to find optimal or quasi-optimal solutions (parameters optimization) for problems in image processing based on evolutionary computation have been extensively addressed in the last decades. Among those techniques, genetic algorithm (GA) techniques try to find the solution over the natural selection of the possible solutions (individuals) among the iterations of the algorithm (generations). In addition, for better spectral and geometric requirements, the image sharpening and fusion methods are developed to obtain higher resolution MS colored images by merging the HR pan image with the LR MS image.

In this paper, section 2 mentions previous methods and algorithms related to our proposed framework. Section 3 introduces the proposed framework for sharpening and enhancing MS satellite images. Evaluated experiments are explained in section 4. Results are discussed in section 5.

II. RELATED WORK

Image Registration is a process of estimating a transformation matrix for accurate geometric matching between images. It is used to produce a set of simulated matched images. The di□erences between matched pixel values and the actual unmatched ones are used to iteratively update theestimation process in each iteration. Successful image reconstruction is dependent on minimizing these image differences. The search for matching transformation can be automated with the use of suitable metric, but it is difficult to determine accurate solution with direct search methods. Accuracy and guaranteed converged search method is needed for satellite image registration. Therefore, in this work the GA-based registration is implemented

to get more accurate transformation parameters for more stable matching process.

In remote sensing, image restoration performed to correct distortions and blurring produced by the imaging systems and the atmosphere. The correction of this problem is not based on only the sensor characteristics, but on the whole conditions of image capturing. Therefore, for each received image an adaptive filter needs to be used. Regularized and projection-based techniques are the most actively approaches to deal with these ill-posed problems due to their iterated algorithms allow a better controlling of restoration [6]. Stark and Oskoui have proposed a POCS method uses some a priori information about the images in the form of restriction or constraint sets [7]. POCS methods can be used to find a common vector f which satisfies these constraints, each of which forms a convex set.

$$F \in C_o = \bigcap_{i=1}^{m} C_i \quad (1)$$

Where the i-th closed convex set $C_i \in R$ denotes the i-th constraint or a priori knowledge on f and m is the number of those sets [8]. If the sets C_i (i = 1,...,m) are closed and convex, and their intersection, C_0 ,is non-empty, the successive projections on the sets will converge to a vector that belongs to this intersection. This vector can be found by alternatively projecting it onto the convex sets C_i via corresponding projecting operator P_{Ci} as

$$f^{(k+1)} = P_{C_m} P_{C_{m-1}} \dots P_{C_1} f(k) (2)$$

Where P_{Ci}means the projection onto convex set $C_i \in R$ in the k-th iteration. The initial guess f(0) can be any vector in R [8]. Several methods were developed to estimate the blur from the image, they are very high computation methods and require user interface, for that blur has been assumed in many researches for simplicity. Therefore, in the proposed framework, GA is implemented to adaptively estimate the blur according to the input image and required measured metrics.

In remote sensing, image fusion combines the low spectral-high spatial resolution images with high spectral-low spatial resolution ones[9]. High pass frequency (HPF) image fusion operates in the spatial domain, which inserts textural details of the higher resolution image into the lower resolution MS image.Fusion weights of the injection model optimized to deliver satisfying spatial and spectral quality[9]. Therefore, inthe proposed framework, GA is used forautomatically weights estimation to get a higher spatial-quality fused image with reasonable spectral image quality.

Genetic algorithm (GA) is amotivated search techniquesimulates biological evolutionary process to solve optimization problems [10]. Instead of searching one point at a time, GAs employ multiple concurrent search pointsto find near-optimal solutions without going through huge searching. Thus, the most significant advantage of GA is its simplicity and huge search space reduction, while guaranteeing the convergence of the solution [11]. It can climb peaks in parallel, reducing the probability of finding local maxima, which is one of the drawbacks of traditional optimization methods [12]. The initial population (P) is created randomly from solution space [13, 14]. Each element in P is a chromosome composed of a list of genes. They go through evolution process by performing some genetic operations. According tothe higher fitness values, strongerchromosome are selected for the next generation. Once the process converged and noimprovement is observed, the elements with the global maximum valueare obtained. The genetic operations of crossover and mutation are implemented as part of the reproduction, example is shown in Figure 1, the genes in two 8-bit chromosomes A and B are exchanged at the cross point 2 from the left. Then two new chromosomes C and D are generated.

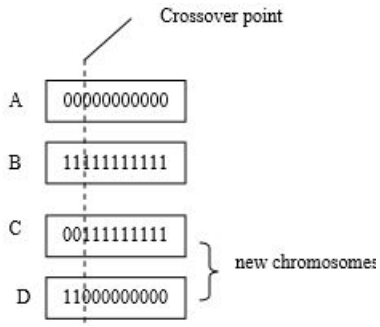


Figure 1: Example of a single point crossover (Picture adapted from [12])

Mutation is a random change of the gene. For example, an 8-bit chromosome '0000 0000' can be mutated at bit 4 to produce a new chromosome '0001 0000'. Mutation introduces new genetic elements into a population to avoid getting trapped at local optima [15], it is used for further diversity.

The overall structure of GA:

- Create the initialization population randomly.
- Use the value of each genotype as estimated parameter in the current operation.
- Constraints are applied to decrease search space.
- Calculate the fitness objective function.
- Select and keep the best genotypes that optimize the fitness function.
- Cross over and/or mutate the genotype to obtain new generation.
- Repeat above steps till convergence.

III. THE PROPOSED GA-BASED IMAGE SHARPENING FRAMEWORK

The main goal of this framework is to improve and stabilize the performance of the image pan-sharpening algorithm by choosing optimal or quasi-optimal parameters through GA-based techniques. In the trials of our work, we implemented many types of mutation and crossover such as simple, uniform, non-uniform, arithmetic, heuristic, single

point and two points to examine which is better in each step of the whole framework, start from registration, restoration till fusion the final process.

GA is proposed in the registration step to estimate the transformation matrix. The fitness function is simply the difference imagebetween the estimated transformed image and the first band of MS image (as a reference), it is defined as following:

$$Minimize: Fit(C_i): \sqrt[2]{mean\big(abs(Y-X)\big)} \quad (3)$$

Where, Ci is genotype, Y and X are the reference and image to be registered respectively.The initial population consists of 30 genotype; using scatter crossover and uniform mutation with rate = 0.01 for generating new generations.The output registration parameters used in warping the input images successfully for optimum matching.For comparison, we implemented forwards additive algorithm (Lucas-Kanade) [16] to estimate the registration parameters for the same input images. In both algorithms we used bilinear pixel interpolation. It helps to calculate the intensity of a transformed pixel with better accuracy. Transformed pixels usually have non-integer coordinates, so by interpolating their intensities we take intensities of neighbor pixels into account. This also helps to avoid mean error oscillations and improve overall minimization performance.

In previous efforts of image restoration as in [17], the blur kernel was estimated by trial and error for simplicity.In our approach; we applied GA to estimate the values of 5×5 blur kernel simultaneously. To apply the algorithm, and due to the difference between images in spectral characteristics, the registered images from previous step are passed into 3×3 high pass filter to generate high-spatial details which are used in POCS image reconstructing. The fitness function is defined as following:

$$Minimize: Fit(Ci): \frac{norm(Y-Y_{prev})}{norm(Y)} \quad (4)$$

Where, C_i is genotype, Y and Y_{prev} are the POCS reconstructed HR image at specific iteration and at previous one.The initial population consists of 10 genotype, the scatter crossover used and the mutation with rate = 0.01 is employed.After running this algorithm, the estimated blur kernel with regards to optimized image quality is used in reconstructing the HR image by POCS method. For comparison, we implemented the same POCS algorithm, but instead of estimating the blur according to some criteria, it is assumed by try and error [17].

For sharpening the up-sampled MS, the HPF fusion injects the spatial details of the POCS-reconstructed HR image to each MS bandusing an automatic GA-based standard deviation-based injection model. The injection weights for the added HR image is a critical parameter. The ideal weight varies with the resolution ratio (R), the high-pass filter size and center value, the preferences of the analyst and the application of the fused image [9]. It is derived as a percentage of the global standard deviation (SD) of each individual MS band. It was found to be in the range from 20 percent to 25 percent (in case R = 2) of the SD [9]. In some cases, the increased weight values visually improve fusion results by reducing false edges; however, it doesn't improve the spatial fidelity. According to many tests, a slight decrease (10 %) in the weight may create efficient fusion results with minimum loss of color distortion.

$$Maximize: Fit(C_i): \sqrt[2]{\sum\sum \frac{(F-API)^2}{p\times q}} \quad (5)$$

Where, C_i is genotype, F is the fused image, API is the Average Pixel Intensity (Mean) of fused image, p*q is the image size. The initial population consists of 10 genotype, the scatter crossover and random mutation with rate = 0.01 is employed. The weights estimated with regards to optimized image quality are used for HPF fusion. For comparing, the same fusion method is implemented, but we used try and error for estimating the weights. For visual comparison, we perform linear histogram match to adapt SD and Mean of the fused MS bands to those of the original MS bands, the sharpened HPF-fused images by proposed work are shown in figures 2 and 4. Beside visual evaluation, measured metrics are used to evaluate the performance of proposed work.The Relative dimensionless global error in synthesis (ERGAS) metric indicates the spectral and spatial quality of the fused image [18]. In case of spectral quality, ERGAS is computed between the fused images and the original MS input ones. However, in case of spatial quality, error iscalculated according to the POCS-reconstructed HR image.

The Structure Similarity (SSIM) index [19] computes the quality by comparing the correlations in luminance, contrast, and structure locally between input and fused images.It is used to measure spectral similarity between the MS image before and after image fusion. Higher values of MSSIM indicate higher spectral quality of the fused image and vice versa. For spatial quality, it measures the similarity between the fused MS image and the POCS-reconstructed HR image.

IV. EXPERIMENTS

We conducted experiments by using two EGTPTSAT-1 satellite datasets. Each dataset consists of one pan (7.8 m resolution) and three MS bands (7.8 m resolution)shown in Figs. 2(a, b) and 4(a, b). The GA-Based registration is performed for geometric matching between all four bands after performing radiometric histogram equalizing. Applying restoration techniques directly on MS bands 1, 2, 3 and the pan band produces a noisy image, due to the difference between bands in spectral characteristics [20]. So we applied the GA-based POCS restoration method to the spatial details (high-pass filtered) extracted from the four bands [20]. At

last, the reconstructed POCS HR image from previous step is fused to each band of the up-sampled MS image according to the proposed GA-based injection model to produce colored sharpened higher resolution MS image (HPF technique); results are shown in Figs. 2f and 4f.For comparing our approach with conventional (conv.) methods, another framework is implemented by using gradient-based motion estimation in registration process and assuming blur kernel and injection weights for restoration and fusion processes in respectively, results are shown in Figs. 2e and 4e. Another method is also used for illustration. it is the duplication of pixels (zero-order interpolation): each original pixel, say at 8 m, provides four new pixels at 4 m resolution, each of them having the same value as their parent pixel as shown in Figs. 2c and 4c, this method is denoted "INT." for zero-order interpolation. In addition, another conventional interpolation method based on cubic convolution is implemented for comparison; it is denoted in figures and tables by “cubic” Figs. 2d and 4d.

The main steps of the proposed work:

1)Selecting an egyptsat acquired image (pan and MS bands) with non-integer (in terms of inter-pixel distances) geometric displacements between any two bands.

2)Histogram matching of the MS bands 1, 2 and 3 with pan band to minimize the spectral difference.

3)Sub-pixel registration of bands 1, 2 and 3 with the pan band by the proposed GA-Based registration method.

4)Extracting the high-frequency spatial details in the four bands by a high-pass filter with size 3X3.

5)Reconstructing an HR image of the high-frequency spatial details extracted in step 4 using the proposed GA-Based POCS restoration method with the registration parameters estimated in step 3.

6)Removing the noise in the estimated HR image from previous step with an adaptive Wiener filter.

7)Using proposed GA-Based HPF fusion method to sharpen the upsampled MS bands using the POCS-reconstructed HR image denoised in step 6.

V. RESULTS AND DISCUSSION

The proposed framework is fine-tuned by means of three parameters: transformation matrix of registration process, blur kernel values for restoration process, and injection fusion weights.An accurate transformation matrix is estimated automatically instead of high computation methods based on gradient (Grad.). Resultsand measured RMSE values (in bold)are shown in Tables1 and 2. Benefits of this method are accuracy, stability of estimation, automated solution and the low computational cost.

Table 1. Estimated registration parameters of first image and their RMSE

	Band1			Band2			Band3		
	dx	dy	rmse	dx	dy	rmse	dx	dy	rmse
Grad.	.45	.41	**14.5**	.12	.5	**13.7**	.43	.46	**15.9**
GA	.44	.48	**11.3**	.02	.53	**12**	.54	.43	**13.9**

Table 2 Estimated registration parameters of second image and their RMSE

	Band1			Band2			Band3		
	dx	dy	rmse	dx	dy	rmse	dx	dy	rmse
Grad.	.48	.63	**9.7**	.84	.16	**9.9**	.71	.54	**11.4**
GA	.49	.59	**9.4**	.81	.18	**9.7**	.69	.57	**9.7**

Table 3 GA-based estimated fusion weights

	Band1	Band2	Band3
First image	.76	.79	.8
Second image	.79	.77	.75

The GA-estimated adaptive weights are shown in Table 3. Investigating the fused image quality of the GA approach; the ERGAS and MSSIM of spatial and spectral values are calculated and averaged over the three bands, Tables 4, 5 show a significantly higher spatial fidelity of GA approach with regard to traditional conventional method such as work in [21] in which parameters such as blur kernel and fusion weights are assumed or estimated by visually try and error. On the contrary, spectral metrics in tables 4, 5 show less fidelity. There is trade-off between spectral and spatial fidelity in this approach. According to the application; user can decide the priority. Evaluating the whole image quality, values of ERGAS spatial (Spa.) and ERGAS spectral (Spec.) metrics are summed, and then their average (Av.) and standard deviation are calculated, the same for MSSIM spatial and spectral metrics as shown in tables 4, 5. In case of GA-Based method; results show better standard deviations (Std.) and averaged value of spatial and spectral metrics more than cubic and conv. methods. A visual analysis indicates an increase in spatial quality of GA method with respect to the original image (Figs 2f& 4f) while maintaining the spectral quality. To evaluate sharpening, line spread function (LSF) is calculated by edge-knife method. Figures 3a, 3b, 3c, 5a, 5b and 5c show a comparison of the measured LSFs between analogues bands of the proposed GA-based fused MS bands and the conventional fused MS bands. The enhancement in the LSF in case of GA approach is observed. the spatial resolution improvement is estimated by the full width half maximum (FWHM) metric. By comparing FWHM of “INT.” curve and that of proposed “POCS-GA”; the enhancement by factor of two. Moreover, a comparison between the

proposed GA-based registration and the gradient-based registration in sense of convergence is shown in Fig. 3d. This figure shows that the proposed GA-based algorithms exhibits faster convergence compared to the conventional gradient-based registration algorithm.

Table 4. ERGAS metrics for 1st& 2ndimages

	1st image				2nd image			
	Spa	Spec	Av	Std	Spa	Spec	Av	Std
Cubic	44.1	33.7	38.9	6.6	33.9	25.9	29.9	5.6
Conv.	42.6	34.9	38.8	6.6	32.9	26.8	29.8	5.7
GA	27.5	43.1	35.3	11.1	17.7	29.1	23.4	7.9

Table 5. MSSIM metrics for 1st& 2ndimages

	1st image				2nd image			
	Spa	Spec	Av	Std	Spa	Spec	Av	Std
Cubic	.94	.97	.95	.02	.97	.96	.96	.01
Conv.	.956	.96	.955	.03	.98	.95	.96	.02
GA	.981	.94	.96	.04	.99	.95	.97	.03

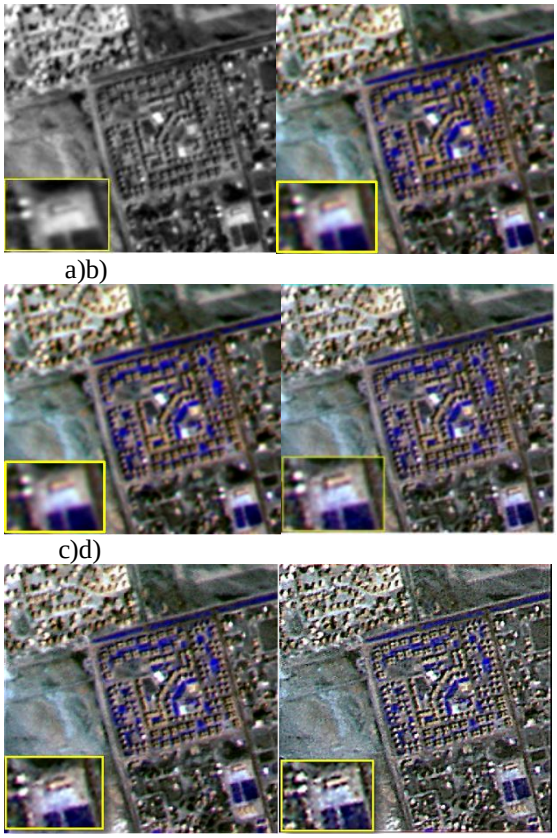


Figure 2:first image; a) Pan, b) MS, c) Zero-order interpolation Image, d) Sharpened MS by Cubic Convolution, e) Sharpened MS by Conv., f) Sharpened MS by Proposed GA-Based Method

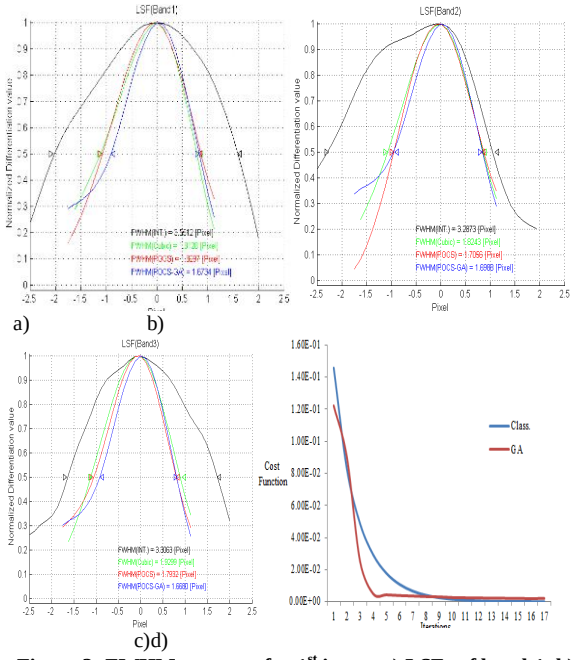


Figure 3: FWHM measure for 1st image a) LSFs of band-1, b) LSFs of band-2, c) LSFs of band-3, d) convergence of classic (conventional) and GA-based registration algorithms

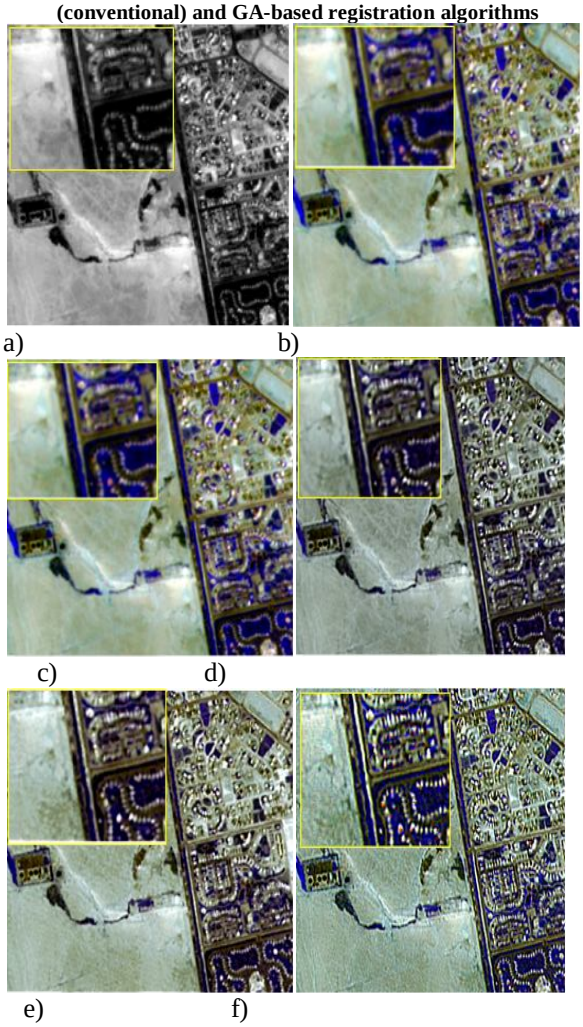
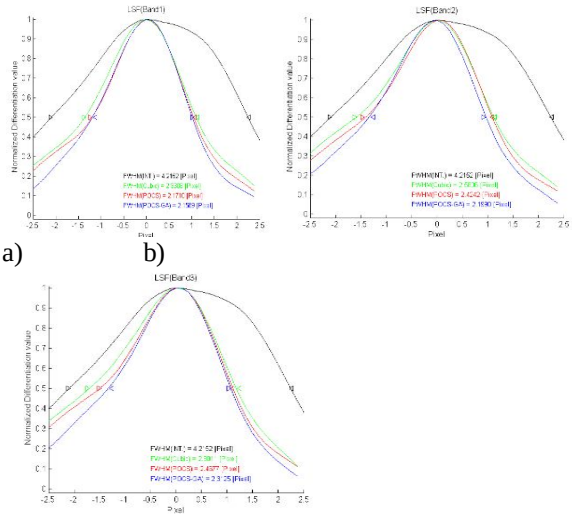


Figure 4:second image; a) Pan, b) MS, c) Zero-order interpolation Image, d) Sharpened MS by Cubic Convolution, e) Sharpened MS by Conv., f) Sharpened MS by Proposed GA-Based Method



a) b)

c)

Figure 5: FWHM measure for 2nd image a) LSFs of band-1, b) LSFs of band-2, c) LSFs of band-3

CONCLUSION

For a successful pan-sharpening using multi-bands satellite images; the sub-pixel image registration is needed to be accurate, the proposed GA-based registration method gives more accurate results than the conventional high-computational gradient-based methods.The image restoration is a challenging highly inverse ill-posed problem, for which there has been limited success in solving in a timely and efficient fashion. Therefore, the proposed GA-based method has been successfully implemented in estimating the blur kernel in the POCS restoration problem. The same for image fusion, the proposed automatic GA-based weights-estimation produces efficientspatial quality while preserving reasonable spectral information. In the proposed work, the ability to incorporate various constraints and the simplicity of the genetic tools in contrary of the complex optimization methods provide a good framework for pan-sharpening and resolution enhancement. The user can select the primitives to guide the reconstruction and discriminate suggested sets of parameters to provide an optimal visual quality image.Simulations and experimental results show that this framework also works in practice

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