A Framework for Satellite Image Enhancement Using Quantum Genetic and Weighted IHS+Wavelet Fusion Method

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***Abstract*—this paper examined the applicability of quantum genetic algorithms to solve optimization problems posed by satellite image enhancement techniques, particularly super-resolution, and fusion. We introduce a framework starting from reconstructing the higher-resolution panchromatic image by using the subpixel-shifts between a set of lower-resolution images (registration), then interpolation, restoration, till using the higher-resolution image in pan-sharpening a multispectral image by weighted IHS+Wavelet fusion technique. For successful super-resolution, accurate image registration should be achieved by optimal estimation of subpixel-shifts. Optimal-parameters blind restoration and interpolation should be performed for the optimal quality higher-resolution image. There is a trade-off between spatial and spectral enhancement in image fusion; it is difficult for the existing methods to do the best in both aspects. The objective here is to achieve all combined requirements with optimal fusion weights, and use the parameters constraints to direct the optimization process. QGA is used to estimate the optimal parameters needed for each mathematic model in this framework "Super-resolution and fusion." The simulation results show that the QGA-based method can be used successfully to estimate automatically the approaching parameters which need the maximal accuracy, and achieve higher quality and efficient convergence rate more than the corresponding conventional GA-based and the classic computational methods.**

***Keywords*—Quantum genetic algorithm (QGA); HIS; fusion; wavelet; registration; super-resolution**

I. Introduction

Image fusion is the process of merging two or more images obtained from two or more sensors for the same scene. The objective is to extract more information from the fused image than information in individual images. In satellite images, the low resolution (LR) multispectral (MS) image are merged with the high resolution (HR) panchromatic (pan) image to obtain the MS HR image by using fusion technique [1]. In the recent years, many fusion methods such as Intensity Hue Saturation (IHS) transform, High Pass Filtering (HPF) method [2], Laplacian pyramid [3] and wavelet transform have been proposed. The stand-alone IHS method is the most commonly used fusion technique because it can convert a standard RGB (Red, Green, Blue) image into (I), (H) and (S) components, the transform, and inverse equations mentioned in [4]. This color space has the advantage of the human beings visual system in which I, H, and S components considered as roughly orthogonal perceptual axes. Therefore, it can add the spectral and spatial information smoothly for satellite images with overlapping spectral sensitivity between pan image and MS image. But this method has a disadvantage that the color quality of the fused image strongly depends on the similarity between the HR pan image and the intensity image (I) of the MS LR image [5]. The gray value distribution of the intensity of the IHS image should be close enough to that of the pan image to preserve the spectral information [6]. However, the difference between the intensity image and the pan image causes a major spectral color distortion. Among the existing fusion methods, wavelet transform based method. It has the advantage of qualified localization in both space and frequency domains [7]. The stand-alone wavelet fusion outperforms other conventional (conv.) fusion techniques, such as IHS, Principal Component Analysis (PCA) in preserving spectral information [8] because it usually injects the high spatial details from the HR image into all three low spatial resolution MS bands. However, these high spatial information in the HR image have gray values different from that of an MS band. This difference may cause some spectral distortion in the wavelet-fused image, the combination between color and spatial details appear unnatural [9]. To better employ the advantages of IHS and wavelet fusion methods and to get over the shortcomings of the two stand-alone methods, researchers has introduced an IHS and wavelet integration fusion in previous work; explained in [10]. In general, it uses the IHS transform to integrate the spectral information of LR MS with the spatial detail information of HR pan to achieve a smooth combination of spectral and spatial information, while wavelet transform is utilized to generate a new image "New Intensity" that has a similar gray values distribution to "I" component of MS and contains the high spatial details of the pan. As illustrated in Fig. 1, the process steps of this method is explained (before image fusion, the MS image is resampled to have the same pixel size as the HR pan by using the cubic interpolation). The integrated IHS with wavelet transforms produces efficient results than either standard methods or stand-alone wavelet-based methods [11]. However, the trade-off is higher complexity and cost [12]. On the other hand, the HR pan image can be reconstructed from multi LR images by applying super-resolution techniques utilizing the subpixel shifts between them. The quality of the reconstructed image depends on the accuracy of subpixel shifts estimation process. Image restoration and interpolation techniques are implemented to obtain the estimated HR pan image [13]. Several techniques have been introduced in many studies such as robust super-resolution (RS) based on bilateral total variations by Farsi [14], iterative back projection (IBP) by Irani [15], projection onto convex sets (POCS) by Stark and Oskoui [16], and structure-adaptive normalized convolution (SANC) by Pham [17]. These techniques use a priori information about the degradation and the imaging system. The key to apply these techniques is to give appropriate values for the parameters utilized in an image processing system designed to achieve some criteria implied by the constraints. Several methods to find optimal or quasi-optimal solutions (parameters optimization) for problems in image processing based on evolutionary computation introduced in the last decades. Evolving solutions rather than computing them is considered a favorable programming approach. 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) [18].

However, another alternative of evolutionary algorithms was introduced: QGA, it is a combination of GA and quantum computing. Quantum computation has attracted researchers concern. There were some efforts to use QGA for exploring search spaces. In this work, we applied the QGA using Spot-4 & Spot-5 data sets; the framework starts with sub-pixel shift registration, then image restoration and finally IHS+Wavelet fusion. All models based on QGA that used for parameters estimation to extract some computational abilities of QGA to perform processing in an effective and an efficient manner. Results compared with those obtained by corresponding GA-based registration, restoration, and IHS+Wavelet fusion methods and also with those got by corresponding classic Computational methods. The objectives of this work as follows:

- Extracting more spatial information from 2 subpixel-shifted images of the same scene by super-resolution.
- Introducing relevant information from multiple images from two sensors in a single image by fusion.
- Improving the image registration by accurate estimation of the sub-pixel transformation matrix.
- Improving blind image restoration by image-dependent estimation of blur kernel instead of assuming.
- Improving fusion by automatic adaptive-weights estimation according to the application.
- Comparing the proposed methods with classic ones by visual inspection, measuring metrics and plotting the Line Spread Function (LSF) curves for estimating the spatial resolution enhancement.

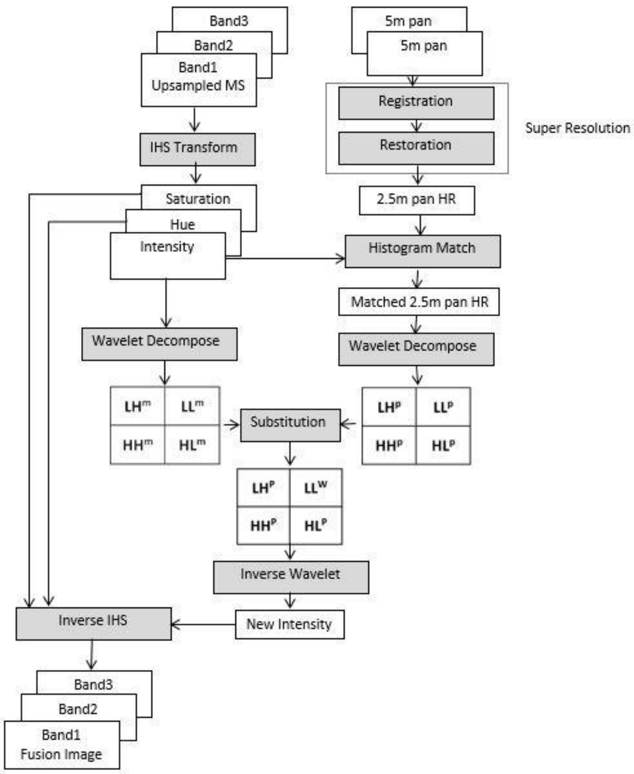


Fig. 1. The IHS+Wavelet fusion steps

This paper is organized as follows. Section 2 explains the quantum genetic algorithm. Section 3 describes the proposed QGA-Based satellite image enhancement framework. Section 4 presents the experiments with different restoration methods. Section 5 discusses the results and the comparison with other classic methods. Finally, conclusion is explained in Section 6.

II. QUANTUM GENETIC ALGORITHM

Unlike classic computing in which the smallest unit (the bit) can be 0 or 1 to represent the data, the quantum computing uses qubit which can be in the "1" state, in "0" state or in any superposition of them [19]. A state of a qubit described as formula:

$$|\Psi> = \propto |0> + \beta|1> \quad (1)$$

Where |0> and |1> represent the bit classical values 0 and 1 respectively, α and β are complex numbers satisfy the condition:

$$|\propto|^2 + |\beta|^2 = 1 \quad (2)$$

$|\alpha|^2$ is the probability to have the value 0 and $|\beta|^2$ is the probability of having the value 1. However, when the 'measure' or 'to observe' is taken, the qubit will converge into a single state. If there is a system of m-qubits, the resulting state space has 2^m dimensions. It is an exponential growth of the state space. This exponential parallelism could lead to exponentially faster convergence than the classical systems. The QGA chromosome is string of N qubits can be represented by:

$$q_j^t = \begin{bmatrix} \alpha_{11}^t \alpha_{12}^t .. \alpha_{1k}^t \ldots\ldots & \alpha_{m1}^t \alpha_{m2}^t .. \alpha_{mk}^t \\ \beta_{11}^t \beta_{12}^t .. \beta_{1k}^t \ldots\ldots & \beta_{m1}^t \beta_{m2}^t .. \beta_{mk}^t \end{bmatrix} \quad (3)$$

Where q_j^t represents the j^{th} chromosome of the t^{th} generation, k represents the No. of the qubit in each gene; m represents No. of genes in each chromosome. Comparing with the traditional GA that uses crossover and mutation to achieve population diversity, in QGA the chromosome values updated by a Q-gate as the following:

$$\begin{bmatrix} \alpha_i' \\ \beta_i' \end{bmatrix} = U(\Delta\theta_i) \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \quad (4)$$

Where α_i & β_i represent the qubit before update, α_i' & β_i' represent the qubit after update and $\Delta\theta_i$ represent the rotation angle. The lookup table of rotation angle in QGA explained in [20]. Therefore, QGA has better search ability as well as convergence speed and the performance of the algorithm will not be affected with a small population size [21].

III. Quantum Genetic-Based Satellite Image Enhancement

The main goal of this framework is to improve and stabilize the performance of the image enhancement methods by choosing optimal or quasi-optimal parameters through QGA-based techniques. The framework consists of registration, then restoration and at last image fusion. The overall structure of the QGA in general:

1) Initialize the population Q(t0); the initial (α, β) of each are equal 1/sqrt(2) [19], that to begin presenting all states with equal probability.

2) Produce P(t) by observing states of Q(t) (extract a classic gene from a quantum gene, it is selected randomly based on the α and β values of the qubit).

3) Evaluate the fitness of every solution of P(t) by applying objective fitness function.

4) Use the best-evaluated solution in next generation as the evolutional goal.

5) Update population Q(t) by quantum rotating gate, that obtain Q(t+1).

6) Store the best solution and its fitness value.

7) Repeat above steps till convergence to an optimum value or till no improving can get.

A. Quantum Genetic-based Image Registeration

QGA is proposed to estimate the registration parameters (transformation matrix). The fitness function is to minimize the error (difference image) between the reference and input (estimated transformed) images. It defined as following:

$$\text{Minimize: Fit}(C_i): \sqrt[2]{\text{mean}\big(\text{abs}(Y - X)\big)} \quad (5)$$

Where, C_i is genotype, Y and X are the input image and the reference image respectively.

In this work, the initial population is selected to be 10 genotype, the registration parameters are estimated with regards to optimized matching between images. Therefore, these values can be used in warping the images successfully. For comparison, the corresponding conv. GA procedures are applied on the same image and with the same fitness function. Also a classic computational conv. registration method; forwards additive algorithm (Lucas-Kanade) as in [22] is implemented. Bilinear pixel interpolation is selected to calculate the intensity of a transformed pixel with better accuracy. So by interpolating their intensities, the intensities of neighbor pixels are taken into account. This is to improve overall minimization.

B. Quantum Genetic-based Image Restoration

Blur kernel is used for restoring the degraded image and reconstructing an HR image from multi LR images by applying super-resolution techniques. In many studies, the values of blur kernel have been determined by the trial and error for simplicity as work in [23]. In our approach; QGA is applied to estimate three unique values of a symmetric 5×5 blur kernel simultaneously. To evaluate the fitness solution, the multi LR images and the estimated registration parameters from previous step are needed to get the HR in each iteration. The fitness function is defined as the following equation:

$$\text{Minimize: Fit}(C_i): \frac{\text{norm}(Y - Y_{\text{prev}})}{\text{norm}(Y)} \quad (6)$$

Where, C_i is genotype, Y and Y_{prev} are the reconstructed HR image at an iteration and at the previous one. The initial population is selected to be 15 genotype. The blur kernel is being estimated with regards to optimized image quality. Then it is used in reconstructing the HR image. For comparison, another GA-based restoration method is applied to the same image with the same fitness function. Also, the same technique is implemented, but instead of estimating the blur kernel according to metrics, it is assumed by try and error.

C. Quantum Genetic-based (IHS+ Wavelet) Image Fusion

Weighting parameters for fusion step are estimated during this framework by using an optimization approach based on QGA searching technique. The “IHS + Wavelet” fusion is implemented in this research by fusing the HR Image reconstructed in the previous step to each band of the up-sampled MS image, it is performed by using an automatic standard deviation-based injection model in order to standardize the method. Increasing the weight value means that the high-spatial details of reconstructed HR image is more intensely incorporated into the resulted fused MS image. In this framework, fusion weights of each MS band are automatically estimated separately by QGA according to the its pixel values and the required standard deviation while preserving the visual spectral information of the colored MS fused image. Weights are estimated according to the application, here in spatial enhancement application, high-spatial details are most required while preserving the spectral information for visual comparison as possible. For implementing QGA, the wavelet component of reconstructed HR image from previous step and wavelet of intensity of IHS of up-sampled MS bands of original image are needed. The fitness function is defined as following equation:

$$\text{Maximize: Fit}(C_i): \sqrt[2]{\frac{\sum\sum(F-API)^2}{p\times q}} \quad (7)$$

Where, C_i is genotype, F is the resulted fused image, API is the Average Pixel Intensity (Mean) of resulted fused image, p*q is the image size. In this work, the initial population is selected to be 5 genotype. The weights are being estimated with regards to optimized image quality. Therefore, these values can be used in IHS+Wavelet fusion step. For comparing, another GA-based IHS+Wavelet fusion method is applied to the same image with the same fitness function. The same fusion method is implemented by using try and error experimentation for estimating the weights. For visual comparison, linear histogram match is implemented to adapt standard deviation (SD) and mean of the fused image bands to those of the original MS.

IV. Experiments

We conducted experiments to demonstrate the proposed QGA-based framework. Two types of datasets "Spot-5 and Spot-4" for the same scenes are used. Spot-5 datasets are two pan 5m-spatial resolution images, Spot-5 satellite features a new dual linear detector array configured as being offset in the focal plane in such way as to provide coincident imagery of the same instantaneous field view with offset by 2.5m on both lines and columns; that produces two pan images definitely shifted by (0.5, 0.5) [24]. Spot-4 dataset is 20 m spatial resolution MS colored image for the same scene with different viewing angle as shown in Fig. 2. The main framework steps:

1) *Estimate sub-pixel shifts between two pan 5m Spot-5 images by the QGA-registration.*

2) *Use the estimated sub-pixel shifts (step1) in estimating an HR pan 2.5m image by applying the proposed QGA-based restoration method (super-resolution technique).*

3) *Co-registering the MS Spot-4 image with the pan 5m Spot-5 image by applying geometric correction (standard Erdas program) to overcome the problem of viewing angle difference.*

4) *Upsample the MS image (from step3) by using cubic interpolation to produce an MS has the same pixel size as the HR pan 2.5m image (from step2).*

5) *Transform the upsampled MS image into IHS components (forward IHS transform).*

6) *Apply histogram matching to the HR pan 2.5m to that of the intensity (I) of the MS.*

7) *Decompose both the matched HR pan 2.5m image and the intensity component (I) of MS (from step5) into wavelet planes respectively (a one-level decomposition is applied).*

8) *Replace the approximation image of the wavelet-transformed matched HR pan 2.5m image (LL_p) by that of the intensity decomposition of MS (LL_m) to inject gray value information of the intensity image of MS into the HR pan image. To avoid an over injection of the intensity information, the LL_p is not completely, but partially, replaced by the LL_m; namely a new approximation image (LL_w) is first generated through a weighted combination of LL_p and LL_m, and then replaces the LL_p of the matched HR pan 2.5m decomposition. Weights are estimated by the proposed QGA-fusion weights estimation. The detail components (LH_p, HH_p and HL_p) of the matched HR pan 2.5m wavelet decomposition remain unchanged. The method to generate the new approximation image LL_w expressed as:*

$$c = w_1.a + w_2.b \quad (8)$$

Where a and b are the approximation images LL_p and LL_m, respectively, and w_1 and w_2 are the corresponding QGA-based estimated weights coefficients.

9) *Perform an inverse wavelet transform to obtain a new intensity has similar gray distribution to that of the intensity image from the IHS transformed MS and contains the same spatial detail of the HR pan 2.5m image.*

10) *Transform the new intensity (step 9) together with the H and S components back into RGB space (inverse IHS transform) to obtain the spatially-enhanced fused MS colored image.*

The whole framework is examined on different restoration methods; such as IBP, RS, POCS and SANC (step 2), the corresponding fusion results are shown in Figs. 5& 6& 7 and 8. The restoration parameters used are such as; step size "α" = 0.05 & regularization factor "λ" = 0.2. Beside visual evaluation, spectral and spatial quality metrics are used in this work to evaluate the performance of proposed work.

V. Results and Discussion

The proposed framework of image enhancement based on QGA optimization is fine-tuned by means of three parameters; Transformation matrix of registration, blur kernel for restoration process and injection IHS+Wavelet fusion weights of the added reconstructed pan HR image to the up-sampled MS bands. To evaluate the accuracy of registration parameters, Root Mean Square Error (RMSE) is calculated as shown in table 1 are compared to the well-known displacement values of 5m pan Spot-5 images (0.5, 0.5) in horizontal and vertical directions. Results show QGA is more accurate than conv. GA-based method and more accurate than the gradient-based (Grad.) registration method implemented as in [22]. Investigating the proposed QGA-based weighted IHS+Wavelet fusion method (estimated weights are presented in table 2), by inspecting the quality of enhanced MS fused images; it is noticed that the proposed method preserves the original spectral properties of the added upsampled MS images to a high degree, although images are subject to spectral distortions during fusion operations. The spectral quality of fused MS images is determined according to the changes in colors as compared to the original MS images those before fusion process. The objective is to obtain the fused image with the optimal combination of spectral characteristics preservation and spatial improvement. In this study, three metrics: peak signal-to-noise ratio (PSNR) [25], ERGAS [26] and The Mean Structure Similarity (MSSIM) index [27] have been used in order to determine the spatial and spectral quality of the MS fused images. Tables 3, 4 and 5 show a significantly higher spatial fidelity of QGA approach with regard to conv. GA-based framework and also to traditional conv. method such as work in [23] in which parameters such as blur kernel and fusion weights are assumed or estimated by visually try and error. The spectral metrics also show better spectral quality in case of QGA approach with regard to GA approach and conv. methods. Evaluating the whole image quality; PSNR values of spatial and spectral metrics are summed, and then their average is calculated, the same for ERGAS and MSSIM spatial and spectral metrics. In case of QGA-based method; results show better averaged values more than GA-based and conv. methods. A visual analysis indicates an increase in spatial quality with respect to the original image (Figs. 5& 6& 7 and 8) while maintaining the spectral quality. To evaluate spatial resolution enhancement, line spread function (LSF) is calculated by edge-knife method. Fig. 3 shows a comparison of the measured LSFs between analogues bands in case of QGA, GA and the conv. Approach (band 1 as an example). We can notice that there is more enhancement in case of QGA. By measuring full width half maximum (FWHM) from LSF curves and comparing with those of classic cubic interpolation method ("cubic" curve); it is obvious that enhancement by factor more than two. Moreover, a comparison between the proposed QGA-based restoration, GA-based method and the conv. method, in sense of convergence is shown in Fig. 4. It shows that the QGA-based method exhibits faster convergence compared to GA-based and classic conv. restoration methods

TABLE I. REGISTRATION PARAMETERS AND THEIR RMSE

	Parameters		**RMSE**	
	dx	***dy***	***dx***	***dy***
Grad.	0.43	0.39	9.1	11.02
GA	0.463	0.44	7.9	8.2
QGA	0.51	0.48	4.6	6.04

TABLE II. IHS+WAVELET FUSION WEIGHTS FOR THE THREE BANDS

Pan weight percentage	**Band1**	**Band2**	**Band3**
GA	0.787	0.80	0.83
QGA	0.807	0.828	0.85

TABLE III. PSNR OF FUSED MS IMAGES USING SEVERAL RESTORATION

PSNR (DB.)		**IBP**	**RS**	**POCS**	**SANC**
Classic	**Spectral**	15.36	15.36	15.64	15.31
	Spatial	4.48	4.38	4.51	4.49
	Average	**9.92**	**9.87**	**10.07**	**9.90**
GA.	**Spectral**	15.54	15.43	15.78	15.54
	Spatial	4.49	4.47	4.53	4.51
	Average	**10.02**	**9.95**	**10.16**	**10.03**
QGA.	**Spectral**	15.70	15.66	15.85	15.62
	Spatial	4.51	4.49	4.57	4.56
	Average	**10.10**	**10.07**	**10.21**	**10.09**

TABLE IV. ERGAS OF FUSED MS IMAGES USING SEVERAL ESTORATION

ERGAS		**IBP**	**RS**	**POCS**	**SANC**
Classic	**Spectral**	23.15	23.15	22.47	23.25
	Spatial	97.98	98.78	97.51	97.69
	Average	**60.56**	**60.96**	**59.99**	**60.47**
GA.	**Spectral**	22.70	22.96	22.16	22.71
	Spatial	97.78	98.05	97.20	97.56
	Average	**60.24**	**60.50**	**59.68**	**60.13**
QGA.	**Spectral**	22.34	22.43	22.00	22.50
	Spatial	97.43	97.60	97.08	97.50
	Average	**59.88**	**60.01**	**59.54**	**60.00**

TABLE V. MSSIM OF FUSED MS IMAGES USING SEVERAL RESTORATION

MSSIM		**IBP**	**RS**	**POCS**	**SANC**
Classic	**Spectral**	0.84	0.85	0.80	0.84
	Spatial	0.90	0.92	0.91	0.93
	Average	**0.87**	**0.88**	**0.86**	**0.89**
GA.	**Spectral**	0.87	0.89	0.83	0.86
	Spatial	0.95	0.98	0.93	0.94
	Average	**0.91**	**0.93**	**0.88**	**0.90**
QGA.	**Spectral**	0.90	0.91	0.86	0.88
	Spatial	0.96	0.99	0.96	0.97
	Average	**0.93**	**0.95**	**0.91**	**0.92**

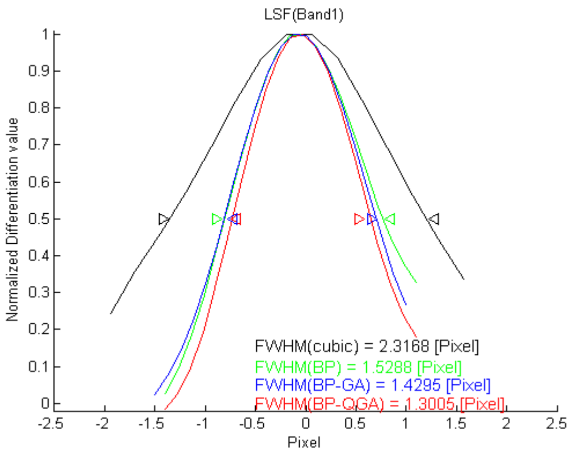
VI. CONCLUSION

The obtained results show that the proposed QGA-based satellite image enhancement framework is much more powerful and efficient compared to the classic GA-Based one. There are two main reasons for this; the first reason is that the quantum encoding of solutions reduces the needed number of chromosomes that achieves reasonable search variance. So, all possible solutions can be represented by only one chromosome at the same time. Therefore, the size of the population does not to be great. It is possible theoretically to use only one chromosome, but in practice, this usually leads to trapping into local optima. Thus, we need little more chromosomes to increase the search space. The second reason is that the advantage of QGA-operations such as rotation gates, that provide in someway a guide for the population individuals, thus the number of necessary iterations to have an acceptable solution is significantly smaller (can be about 60 iterations), and therefore that increase convergence rate. On the other side, benefits of QGA and GA methods in comparison to traditional computational methods are accuracy, the stability of estimation "convergence," automated solution, and the low computational cost. According to the obtained results, the proposed QGA-based method assures accuracy, convergence and better visual image enhancement, it offers very effective solutions for the studied problem. In proposed work, our focus has been to introduce a low-complexity estimation algorithm for using in enhancement MS satellite image. We have shown that the proposed QGA-based registration algorithm rivals many of the more complex state-of-the-art gradient-based motion estimation algorithms. Also we demonstrated that QGA optimization technique can be applied to estimate blur kernel dependent of the image itself instead of assuming or try and error technique in various restoration methods (IBP, RS, POCS, and SANC). Also for implementing the weighted IHS+Wavelet fusion, QGA can be used successfully in the automatic estimation of adaptive injection weights. Simulations and results show that this framework also works in practice.

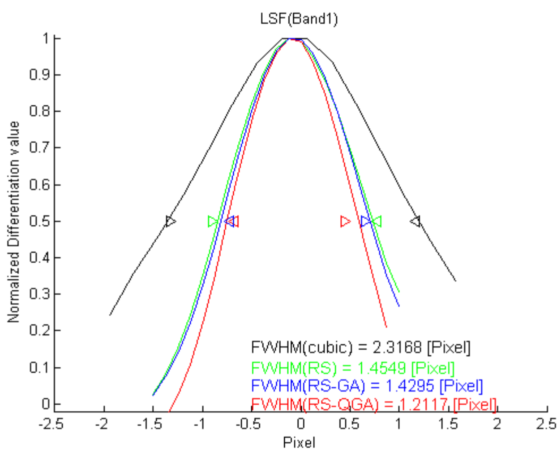
a)

b)

Fig. 2. a) SPOT-5 5m pan image. b)SPOT-4 20m MS image



a)



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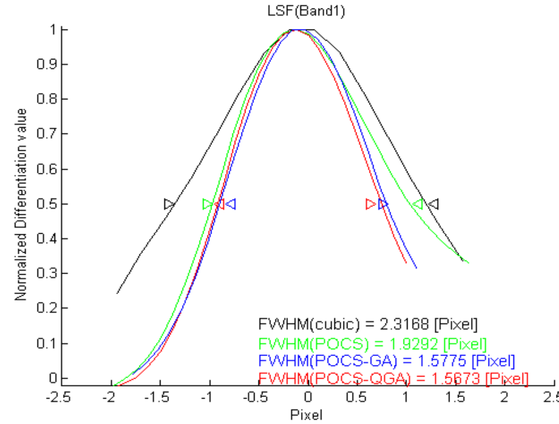
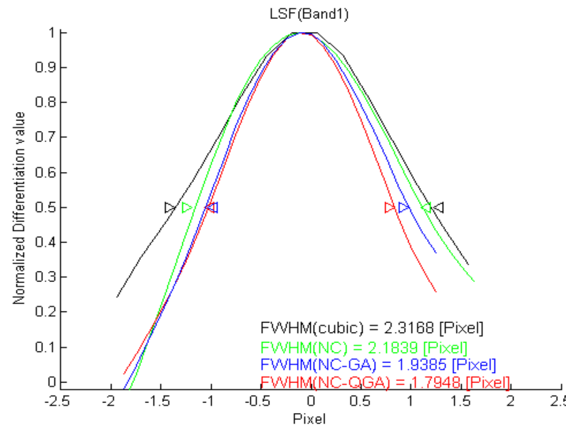


c)



d)

Fig. 3. LSF curves of fused image"band1" in case of these restoration methods a) IBP b) RS c) POCS d) SANC

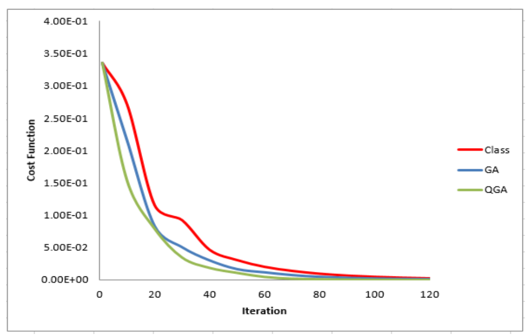


Fig. 4. Convergence rates of Classic, GA, and QGA-Based POCS restoration method

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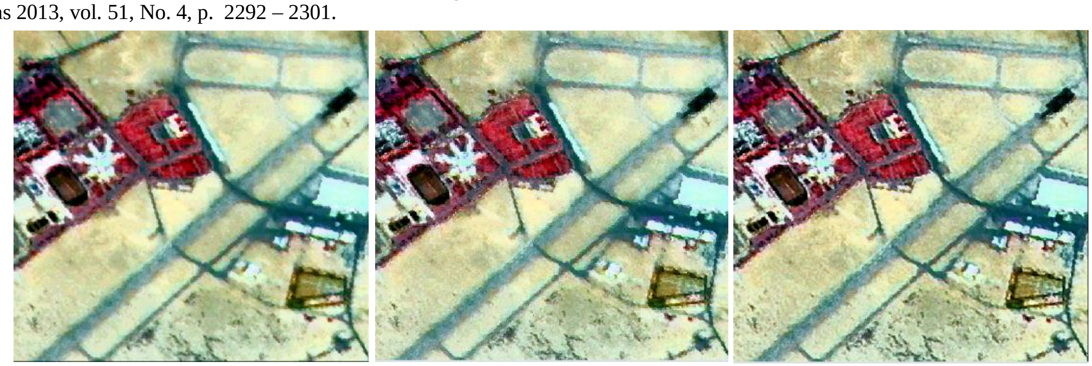
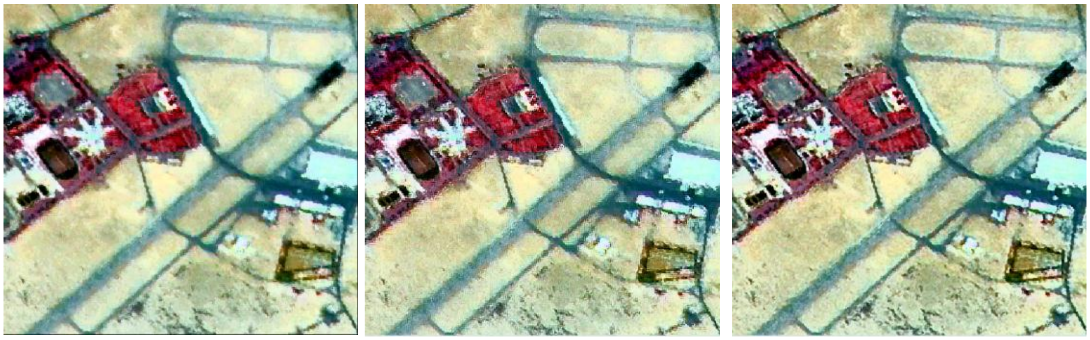


(a) (b) (c)

Fig. 5. Fused MS images in case of IBP restoration. (a) Classic (b) GA. (c) QGA



(a) (b) (c)

Fig. 6. Fused MS images in case of RS restoration. (a) Classic (b) GA. (c) QGA

(a) (b) (c)

Fig. 7. Fused MS images in case of POCS restoration. (a) Classic (b) GA. (c) QGA

(a) (b) (c)

Fig. 8. Fused MS images in case of SANC restoration. (a) Classic (b) GA. (c) QGA