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Remote sensing image fusion using transform domain based on optimization algorithms

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ABSTRACT

With the rapid development of technology today in different fields like military, medicine, robotics, remote sensing, finding underground sources, target tracking, target identification, microscopic imaging, and security applications are need clearer and more meaningful images. Sometimes images from a single sensor are not enough for analysis. For this reason, images taken by different sensors and different features are used together. For this purpose, image fusion (Pan-sharpening) has got great importance. The image obtained by fusion methods contains more meaningful and clear information. In this study, metaheuristic algorithms are used to sharpen the Multispectral (MS) image with a Panchromatic (Pan) image in remote sensing. In this study, the coefficients obtained from Curvelet and Laplacian Pyramid transformations are using with weights that are generated by Particle Swarm Optimization (PSO) and Bat Algorithm (BAT) in the fusion process. A fused image has been successfully achieved by preserving the spatial information of the high-resolution Pan image and the color information of the low-resolution MS image. The obtained results have had a clearer, brighter, and richer edge information. Visual and quantitative comparison of the obtained results were also evaluated.

1. INTRODUCTION

Image Fusion process aims to combine images from more than one sensor at the same time and belong to the same region, thereby improving the image quality. Image fusion is used in many applications. With the emergence of new sensors and the advancement and development of technology and hardware, it is possible to analyze and process real-time data in image fusion. Many different methods, especially Artificial Intelligence (AI) algorithms, are used to increase the image quality of fusion applications. Today, with developing technologies and decreasing costs, satellite images are used in many areas. However, nowadays, data can be received from sensors on satellites at certain frequency ranges and certain resolutions. For this reason, the fusion process is used to obtain more robust and more informational satellite images. In remote sensing, the Image fusion is the process of combining high spatial resolution panchromatic (Pan) image with low-resolution Multispectral (MS) image, which are recorded simultaneously from different satellites (Abas et al. 2015). It is aimed to obtain a single image containing complementary information by detecting the features from two different images and this process is called pan-sharpening. In this study, Particle Swarm Optimization (PSO) and Bat Algorithm (BAT) were used to determine the weights in the fusion process with the coefficients obtained from Curvelet and Laplacian Pyramid transformations. In the study, the proposed method was evaluated by using Landsat-7ETM + satellite images. The proposed technique was compared visually and quantitatively.

2. MATERIAL AND METHOD

2.1. Laplacian Pyramid (LP)

Laplacian Pyramid (LP) provides low pass filtering and subsampling images in the image analysis. LP is an extension of the Gaussian Pyramid (GP). Different frequency bands are used in LP instead of a single low pass filter. Each level of LP is obtained by calculating the difference between the signal at the top level of GP and each lower resolution level of GP. LP Transformation is obtained by applying Filter to the previous level of the GP, then taking the difference between this level and the signal "Eq. 1" (Burt and Adelson 1983; Colores-Vargas et al. 2013; Gupta 1999; Wang and Chang 2011).

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$$G_l(i,j) = \sum_{x=-2}^{2}\sum_{y=-2}^{2} w(x,y)G_{l-1}(2i+x, 2j+y) \quad (1)$$
$$l \in [1,N), i \in [0, X_l), j \in [0, Y_l)$$

Here, G_l is Gaussian pyramid, $w(x,y)$ is the Gaussian weighting function at low pass filters. The source image in the initial layer is the G_0 and N is the number of the Gaussian layers; X_l and Y_l represented the number of columns and rows in the i^{th} layers of the pyramid.

The second stage Laplacian Pyramid decomposition can be calculated as given in "Eq. 2".

$$LP_L = f(x) = \begin{cases} G_l - G_{l+1}^*, & L \in [0, L) \\ G_l, & l = L \end{cases} \quad (2)$$

Where G_{l+1}^* is Gaussian expanded of G_l. LP_L is the Laplacian pyramid and l is the l-th level decomposed; L is the number of LP levels.

2.2. Curvelet Transform (CVT)

The Curvelet transformation was first described by Candès and Donoho (Candes and Donoho 2000). To solve the problem limitation of Gabor and Wavelet transform. It's suitable for mapping edges in image processing problems. Mathematically, it is used for the analysis of big data set and remove the noise. In this work we used a 2-D discrete CVT version implemented fast Fourier Transform and proposed by Candès et al. in 2006 (Candes et al. 2006) "Eq. 3".

$$C(j,l,k) = \frac{1}{(2\pi)^2}\int \hat{f}(\omega)\, \bar{\varphi}_{i,j,k} d(x) = \frac{1}{(2\pi)^2}\int \hat{f}(\omega)\, U_j(R_{\theta_i}\omega) exp\left[i < x_k^{(i,j)}, >\right] d\omega \quad (3)$$

Where $\hat{f}(\omega)$, is the Fourier coefficients and i, j is the index of the pixel image; θ is orientation in the range and $\hat{U}$ is a parabolic window, φ scale of coefficient, $C(j,l,k)$ is the CVT coefficient (Starck et al. 2001).

2.3. Fusion With Metaheuristic Algorithms

2.3.1. Parameter selection with PSO

The Particle Swarm Optimization (PSO) algorithm was purposed by Kennedy and Eberhart (Kennedy and Eberhart 1995) in 1995 to solve a complex nonlinear problem. PSO is started with a group of random solutions (particles) and populations, each particle updates to find an optimal solution. At each iteration, each particle is updated according to the two "best" values. The first of these is the best fitness value a particle has ever found. Also, this value is kept in memory for use later and is named as "pbest", the other best value is obtained so far by any particle in the population, and it is the solution with the best fitness value in the group. This value is the global best particle and is called "gbest". Every particle in the PSO Each particle in the PSO looks for the best solution. The position and velocity are determined by "Eq. 4" and "Eq. 5" (Lin et al. 2015)

$$V_l^{k+1} = \omega \times V_l^k \times C1 \times rand \times (Pbest_l^k - X_l^k) + C2 \times rand \times (Gbest^k - X_l^k) \quad (4)$$

$$X_l^{k+1} = X_l^k + V_l^{k+1} \qquad , l = 1,2, \ldots Q \quad (5)$$

Where V_l^{k+1} is velocity and X_l^{k+1} is a position of l^{th} particle in iteration $k+1$. *Pbest* is the best value of fitness function achieved by i^{th} particle before iteration k and *Gbest* is the best fitness function value achieved so far by any particle. *c1* and *c2* acceleration coefficients, *rand* is a random variable between [0, 1], and ω is represented the inertia weight factor used to provide well balanced mechanism between global and local exploration abilities.

2.3.2. Parameter selection with BAT

Bat algorithms is a swarm intelligence based algorithm. It is echolocation behavior inspired to locate their food and prey, it is an algorithm proposed by Mirjalili et al. in 2010 and it is a metaheuristic algorithm used to solve many different problems (Mirjalili et al. 2014; Yang 2010a, 2010b; Yildizdan and Baykan 2020). Every bat in the population uses a form of radar called "echolocation" to locate and communicate with their prey. Bat echolocation is a perceptual system. It is a perceptual system in which a series of loud ultrasonic waves are released to create an echo. These waves return with various sound levels that enable bats to find specific prey. Velocity and position and they are updated using "Eq. 6-8".

$$f_i = f_{min} + (f_{max} - f_{min})\beta \quad (6)$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_*)f_i \quad (7)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (8)$$

Where β is a random vector, the frequency f is in a range $[f_{min}, f_{max}]$ and it is velocity increment. And v_i is the velocity at position x_i with time iteration t.

The parameters of the PSO and BAT are given in "Table 1", below.

Table 1. Parameters of PSO and BAT for fusion

	PSO	BAT
Population size (s)	40	40
Inertia weight (w)	0.1	X
Max. Iteration (iter)	40	40
Learning constants	Constants c1=c2=2	X
Parameter value Frequency	X	Frequencies f_{min}=0 and f_{max}=2
Initial Pulse rate (r)	X	0.5
Initial Loudness (A)	X	0.25
X: Not parameter value		

2.4. Image Fusion

In image fusion, first, the source images are decompositions into low and high-frequency sub-image components by one of the transformation methods such as LP or CVT.

High-frequency subband images reflect detailed components and contain edge detail information from different directions and scales of the source image. On the other hand, low-frequency subband images indicate the component representing the main information of the source image. After decomposed; the fusion rule in the high-frequency domain is the absolute maximum rule "Eq. 9", and the average or weighted average rule is commonly used in the low-frequency domain "Eq. 10".

$$CF_{ij}^{H} = \begin{cases} CA_{ij}^{H}, & CA_{ij}^{H} > CB_{ij}^{H} \\ CB_{ij}^{H}, & CA_{ij}^{H} < CB_{ij}^{H} \end{cases} \tag{9}$$

$$CF_{ij}^{L} = \frac{1}{2}\left(CA_{ij}^{L} + CB_{ij}^{L}\right) \tag{10}$$

In "Eq. 9", where CF_{ij}^{H} is high-frequency fusion image coefficient, CA_{ij}^{H} and CB_{ij}^{H} are high-frequency source images coefficients. In "Eq. 10", where $\mathrm{CF}_{\mathrm{ij}}^{\mathrm{L}}$ is a low-frequency fusion image coefficient, $\mathrm{CA}_{\mathrm{ij}}^{\mathrm{L}}$ and $\mathrm{CB}_{\mathrm{ij}}^{\mathrm{L}}$ are low-frequency source images coefficients.

The fusion rules are very important to fusion quality because they control the contrast and intensity of a fused image. Therefore, a new fusion rule for the low-frequency band has been proposed in this study to obtain better image fusion.

Instead of taking the average of the coefficients of the source images in the low-frequency band, image-based adaptive-weighted coefficients are produced using metaheuristic algorithms, and fusion was performed "Eq. 11".

$$CF_{ij}^{L} = \frac{\left(\omega 1 \times CA_{ij}^{L} + \omega 2 \times CB_{ij}^{L}\right)}{\omega 1 + \omega 2}, \omega \in (0,1) \tag{11}$$

The optimization algorithm, it is aimed to obtain $\omega 1$ and $\omega 2$ coefficients that minimize the mean square error (RMSE) "Eq. 14" while maximizing the entropy (EN) "Eq. 12" and correlation coefficient (CC) "Eq. 13".

$$Entropy = -\sum_{i=0}^{255} p(i) \times \log_2(p(i)) \tag{12}$$

In "Eq. 12", p(i) is the probability value of the brightness of the fused image.

$$CC = 1/2\left(\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(I_1(i,j)-\bar{I}_1)(F(i,j)-\bar{F})}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(I_1(i,j)-\bar{I}_1)^2}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M}(F(i,j)-\bar{F})^2}} + \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(I_2(i,j)-\bar{I}_2)(F(i,j)-\bar{F})}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(I_2(i,j)-\bar{I}_2)^2}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M}(F(i,j)-\bar{F})^2}}\right) \tag{13}$$

$$RMSE = 1/2\left(\sqrt{\frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\left(I_1(i,j)\right)-F(i,j)\right)^2} + \sqrt{\frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\left(I_2(i,j)\right)-F(i,j)\right)^2}\right) \tag{14}$$

In "Eq. 13" and "Eq. 14" the I1 and I2 are input images and Fi is the fusion image. M, N are the image dimensions.

Accordingly, the linear combination given in "Eq. 15" was used for the multi-objective function (Rao 2009)

$$f(x) = (\alpha_1 * CC) + (\alpha_2 * Entropi) + (\alpha_3 * 1/RMSE) \tag{15}$$

The objective function is given in "Eq. 15", as well as α1,α2, and α3, are tested for different values and the best results are taken as α1=α2=0.25 and α3=0.5. With the proposed methods the meaningful information was transferred from the source images to the fusion image, and better results were obtained. In this study, the parameters of the objective function ("Eq. 15") were optimized with PSO/BAT. The flow diagram of the proposed method is given in "Fig. 1". The steps of the proposed method can be summarized as follows:

Step1: Read the remote sensing image1 (MS) and image2 (Pan).
Step2: Source images (MS, PAN) are converted to LP/ CVT space to obtain the Low and High-frequency bands for each image, respectively.
Step3: Apply the fusion rule in "Eq. 11" with the coefficients and weights (w1, w2) generated by the PSO/ BAT for each region in the low-frequency bands of LP/ CVT.
Step4: Fused high-frequency coefficients using maximum selection fusion rule defined in "Eq. 9".
Step5: Using the last obtained coefficients to get a fused image by applying the inverse LP / CVT transformation.

3. EXPERIMENTAL RESULTS

Remote sensing data sets used in fusion study are Landsat-7ETM + MS and Landsat-7ETM + PAN satellite images. Detailed information about the features of these images is given in "Table 2" (Saeedi and Faez 2011).

Table 2. Landsat-7ETM+ satellite images features

Sensor	Spectral Band (Spectral resolution) (μm)		Spatial resolution (m)	Radiometric Resolution (m)	Image Size
Landsat -7ETM+ (MS)	1	450–515 (Blue)	28.5	2	7348 x 6208
	2	525–605 (Green)	28.5	2	
	3	630–690 (Red)	28.5	2	
	4	760–900 (NIR)	28.5	2	
	5	1550–1750(MID-IR1)	28.5	2	
	6	2080–2350(MID-IR2)	28.5	2	
Landsat -7ETM+ (Pan)	1	520–920nm (Pan)	28.5	2	14696 x 12416

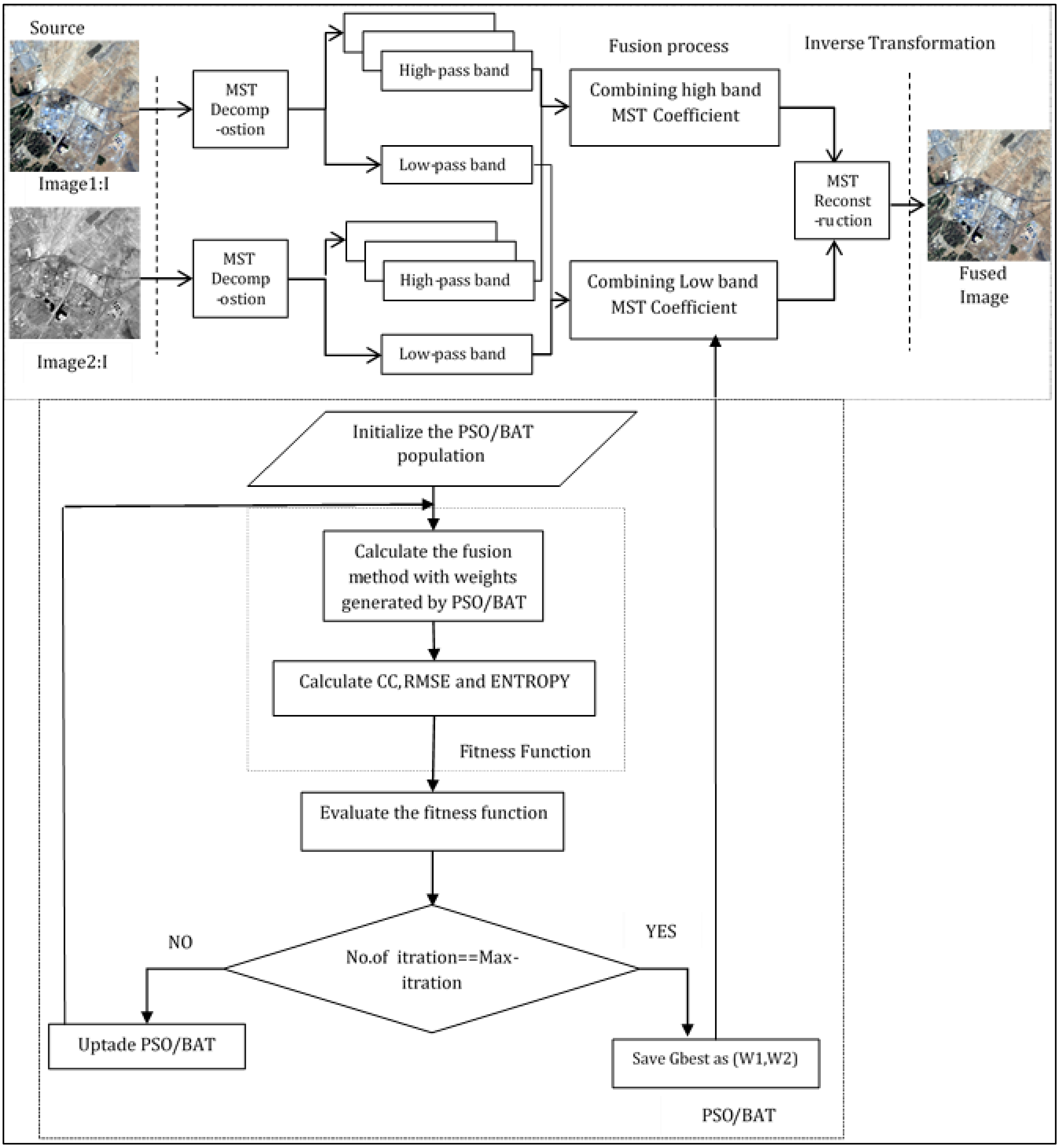


Figure 1. The image fusion process step with PSO and BAT algorithms

In measuring the success of the fusion image obtained from the fusion processes, while the resulting images are expected to preserve spectral values, on the other hand, quality analyzes need to be made quantitatively to increase the spatial resolution. To compare the results of experiments, three quality metrics ERGAS (Relative Dimensionless Global Error in Synthesis) (Wald 2000), RASE (Relative average spectral error) (Ranchin and Wald 2000) and CC (CC-Correlation Coefficient) (Zhou et al. 1998) were used. The results obtained are given in "Table 1" and the result of the satellite images is given in "Fig. 2".

Table 3. Fusion Test Results

Fusion Methods	ERGAS	RASE	CC	Weights
CVT	3.4110	13.5698	0.9293	$w_1 = 0.5$ $w_2 = 0.5$
CVT + PSO	2.6735	11.9325	0.9501	$w_1 = 0.59$ $w_2 = 0.41$
CVT + BAT	2.5726	10.2362	0.9637	$w_1 = 0.62$ $w_2 = 0.38$
LP	2.4232	10.9564	0.9590	$w_1 = 0.5$ $w_2 = 0.5$
LP + PSO	2.1927	10.0702	0.9663	$w_1 = 0.51$ $w_2 = 0.49$
LP + BAT	**1.9978**	**9.3303**	**0.9718**	$w_1 = 0.324$ $w_2 = 0.676$

1. Orijinal Pan image

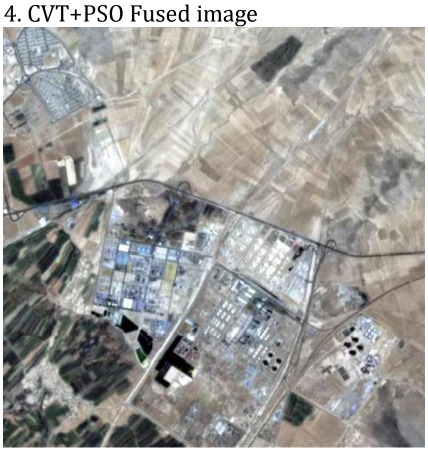
2. Orjinal MS image

3. CVT Fused image

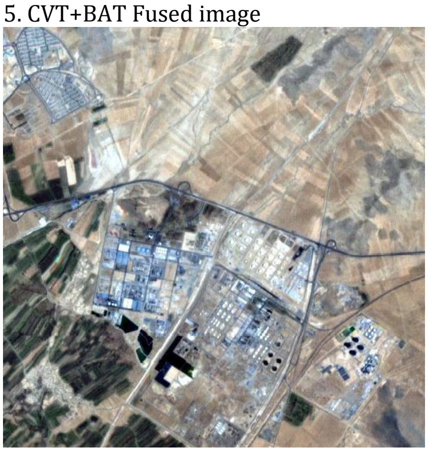
4. CVT+PSO Fused image

5. CVT+BAT Fused image

6. LP Fused image



7. LP+PSO Fused image



8. LP+BAT Fused image

Figure 2. The results of satellite images

4. CONCLUSION

In this study, for combining Landsat-7ETM + MS and Landsat-7ETM + PAN satellite images a fusion method LP and CVT transformations, based on PSO and BAT algorithms are proposed. In the literature, generally, most of the standard fusion methods (weights are taking equal values) usually leading to loss of contrast in the fused image. However, this problem has been solved by the weights are optimized in the best way in the proposed method. In the study, the proposed method was evaluated using Landsat-7ETM + satellite images. In general evaluation, the best result was obtained using the LP + BAT fusion method.

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