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IHS Image Fusion Based on Gray Wolf Optimizer (GWO)

Sapan Jabar Faqe Ahmed [a*], Dleen Mohammed Salih [b]

[a] *College of Engineering- Geomatics dep, Salahaddin University, Erbil, 44002, Iraq*
[b] *College of Engineering- Geomatics dep, Salahaddin University, Erbil, 44002, Iraq*

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ABSTRACT

Satellites may provide data with various spectral and spatial resolutions. The spatial resolution of panchromatic (PAN) images is higher, but the spectral resolution of multispectral (MS) images is greater. There is Satellite sensors limitation for capturing an image with high spatial and spectral resolution, due to the hardware design of the sensors. Whereas many remote sensing, as well as GIS applications, need high spatial and spectral resolution. Image fusion merges images of different spectral and spatial resolutions based on a certain algorithm. It can be used to overcome the sensor's limitation and play an important role in the extraction of information. The standard image fusion approaches lose spatial information or distort spectral characteristics. Optimizations of fusion rules can overcome and degrade the distortions as the fusion core is the image fusion rules. In this paper, the Grey Wolf Optimizer (GWO) is used to find the optimal injection gain, as most distortions in image fusion are caused by the extraction and injection of spatial detail. Both qualitative and quantitative metrics were utilized to evaluate the quality of the merged image. The mentioned metrics that were used commonly for evaluation of image fusion results support the proposed algorithm for image fusion as the output image was qualitatively and quantitatively growth. In the future the proposed method can be updated by increasing the objective function dimensions to two or three for getting a best fused image.

1. Introduction

Remote sensing applications have improved significantly in recent decades in various research fields, including land-cover classification [1] and change detection [2]. The electromagnetic bandwidth of the spectral signatures acquired by the sensor is referred to as spectral resolution in remote sensing images, while spatial resolution is the actual ground area recorded by one pixel. A high spectral resolution is essential for land cover identification, and a high spatial resolution is particularly important for accurately describing the forms and structures of objects in images [3]. In order to meet the needs of various applications, obtaining satellite images with high spectral and spatial resolutions is very important. Collecting energy over a larger instantaneous field of view (IFOV) reduces spatial resolution while collecting it over a larger bandwidth reduces its spectral resolution.

Earth observation satellites, for instance, may gather two types of data at the same time to maintain a specified Signal-to-Noise Ratio (SNR) rate, panchromatic (PAN), and multispectral (MS) images [4]. Generally, a PAN image has a higher spatial resolution than the MS image, but the MS image has a higher spectral resolution than the PAN image. Because of this trade-off between MS and PAN image resolutions, it may be challenging to maintain both spectral and spatial resolution in a single image.

* Corresponding author: Sapan Jabar Faqe Ahmed ; sapan.ahmed@su.edu.krd ; +9647501183902

Nowadays, Pan and MS images can be obtained in a bundle by several commercial optical satellites such as IKONOS, Orb View, Landsat 8, SPOT, Quick Bird, and WorldView-2 [5]. Pan-sharpening, which is the fusing of a low-spatial-resolution MS image with a high-spatial-resolution Pan image to generate an MS image with the same spatial resolution as the Pan image, can be utilized to meet the requirements for images with high spatial and spectral resolutions in applications. Pan-sharpening products have been found to have a high potential for improving classification accuracy and visual interpretation [3].

The number of algorithms has increased over the years, and it has become a challenge to organize and present the various possibilities of fusing remote sensing images. In particular, it has become challenging to identify the various algorithms since they often appear under different names. This is due to the fact that many fusion algorithms have been implemented in commercial software. Different software providers chose different names to supply the same thing. Another difficulty in listing available algorithms occurs in identifying who originated the approach because, over the years published research on the development of new algorithms has not been cited by the originator.

Most pansharpening processes may be broken down into two steps: spatial detail extraction and spatial detail injection. The spatial detail extraction stage is responsible for extracting meaningful spatial information from the high-resolution Pan image. The spatial detail injection step determines how the retrieved spatial details may be injected into the upsampled MS image.

In general, spatial details are retrieved by subtracting the Pan image from its low-pass approximation. Pansharpening methods are roughly classified into two types based on how the low-pass approximation of the Pan picture is calculated [6]: the linear combination approximation (LCA) methods and the spatial filter approximation (SFA) methods. The LCA methods compute the low-pass approximation by a weighted average of the MS bands. Some popular methods of this class are the Brovey transform [7] and the component substitution (CS)-based methods, including principal component analysis [8] and intensity–hue–saturation (IHS) [3, 9].

IHS technique converts a color image from RGB to the IHS color space, and the “I” band is replaced by the panchromatic image. In general, the stronger the correlation between the Pan image and the replacement component, the less spectral distortion will generate. Before the substitution, histogram matching of Pan to the chosen component is conducted. The procedure is finished by reversing the data to its original MS space via the inverse transformation [5]. Because of their ease of computation, excellent spatial resolution, and efficiency, IHS-based algorithms are often employed. The fused image results in high spatial resolution and low spectral resolution [10].

For overcoming the spectral distortion, many researchers tried in this field: a new formalization of the CS approach was proposed by [9] and then analysed other subsequent works [11, 12]. It was shown that under the hypothesis of a linear transformation and the substitution of only a single nonnegative component, the fusion process could be obtained without the explicit application of the forward and backward transformations but by a proper injection scheme as most color distortion will cased through inverse RGB computation [5].

The result of this new formalization is overcoming of spectral distortion but the spatial resolution of fused image is still require some reviewing for getting better result, for this reason some other researches was done:

An adaptive IHS (AIHS) was proposed by [10], this method produce high spectral resolution by finding best method for calculating (I), extracts the edges of panchromatic image and combine it with the multispectral image to increase the spatial and spectral quality.

The above mentioned approach was criticized by [13] and mentioned that AIHS fusion result is still spectrally distorted and mentioned that the problem of the AIHS is the edge extraction from the pan and injection it equally to the deferent bands of MS, so proposed an improved AIHS (IAIHS) method for overcoming the AIHS problem. The amount of spatial details injected into each band of the MS image is suitably decided by a weighting matrix created on the basis of the edges of the Pan and MS images as well as the proportions between MS bands.

Some other researchers [14] using optimization algorithms as Particle Swarm Optimization (PSO) for extraction and injection the optimal amount of detail map. In the study the author mentioned the detail map with fixed weights can cause several distortions and for eliminate this distortion an adaptive framework to compute the injection detail maps in each MS bands was proposed. In this study, we attempted to reduce spectral and spatial distortion in image fusion results by utilizing a new optimization algorithm in the field of pan sharpening for deciding on the injection gain weight of spatial detail.

One of the major flaws in image fusion approaches is the lack of a reliable metric for evaluating fusion outputs. Several attempts have been undertaken to objectively represent the human perception system. Due to the lack of a High-Resolution MS (HRMS) image, two generic methods are proposed to address this issue. The fusion framework is conducted in downscaled versions of the input data in the first method, and the original MS data is used as the reference image. On the other hand, the fusion process is carried out in the full-scale scenario in the second method, and no reference quality metrics are used to evaluate the fusion outcomes [4].

Many metaheuristics approaches were applied to image fusion to improve the performance of the different image fusion approaches [15]. Solving an optimization problem typically means finding optimal values for the decision variables to maximize or minimize a set of objective functions [13].

This research proposes a novel framework for the pansharpening issue, which is classified as IHS-based. This technique aims to identify a suitable objective function for estimating the appropriate injection gain of spectral bands in an LRMS. We choose the grey Wolf Optimizer as optimization algorithm as it requires less variable changing and less iteration numbers for finding the optimal value and the Relative Dimensionless Global Error (ERGAS) measure as objective function for this purpose was selected because it can better depict the nonlinear link between the detail maps of CS-based techniques.

2. Mathematical Background

The previously described LCA approach produces a fused image with high geometrical quality of spatial information but with potential spectral problems. However, if the spectral combination of bands is optimized for the spectral quality of pan-sharpened products, the result of fusion will be more adaptive than standard methods.

The main difference between IHS and BT is how spatial features are weighted before injection, not how they are derived from the Pan image. Regardless of how spatial features are collected, their injection into the interpolated MS bands may be balanced by appropriate gains, which may be different for each band and perhaps space-varying, i.e., a different gain for each pixel [5].

A general formulation of the IHS fusion scheme is given by

$$\acute{M}_k = M_k + g_k\,(P - I) \qquad (1)$$

In which: $\acute{M}_k$ is the multispectral image after pan sharpening.

M_k is the original multispectral image.

k indicates the k^{th} band, $g = [g1,\ldots gk, \ldots, gK]$ is the vector of the injection gains.

While I is defined as:

$$I = 1/3(B+R+G) \qquad (2)$$

Where: R, G, and B are RGB bands.

The injection gain for BT is as follows:

$$g_k = \frac{Mk}{I} \qquad (3)$$

P is the panchromatic band after histogram matching to spatial detail component of Mk and can be obtained as follow:

$$P = [Pan - \mu(Pan)] * \frac{\sigma(I)}{\sigma(PL)} + \mu(I) \qquad (4)$$

Where: σ represents the standard deviation.

μ is the Mean value of pixel values.

PL is a panchromatic band after performing a low pass filter.

By substitute equation 3 in 1, the general formula will be as follow:

$$\acute{M}_k = M_k + \left(\frac{M_k}{I}\right).(P - I) \quad (5)$$

For getting a better result, the following formula is proposed depending on the existed original algorithm for IHS fusion technique:

$$\acute{M}_k = M_k + \left[\left(\frac{M_k.w_k}{I}\right).(P - I) + (w_k\ PH)\right] \quad (6)$$

Where: w_k is the optimal weight of each multispectral band.
PH is the panchromatic band after applying a high pass filter.
In this paper the optimization algorithm will apply to equation (6) for finding the optimal weight (w_k) of MS bands before injection to LMS.

3. Gray Wolf Optimizer

Grey wolf optimizer is a neoteric meta-heuristic optimization algorithm designed, formulated mathematically, and coded by [16]. This meta-heuristics optimization approach was inspired by the hunting behavior of grey wolves. To hunt their prey, grey wolves use a unique approach in which a leadership hierarchy is established amongst packs of wolves [17]. This leadership hierarchy Figure (1) includes a top-level wolf known as alpha, a wolf at the next level known as beta, a wolf at the next subsequent level known as delta, and omega types of wolves considered at the bottom level, with the top three hierarchies considered as the best three solutions and calculated by equation (7) during this algorithm.

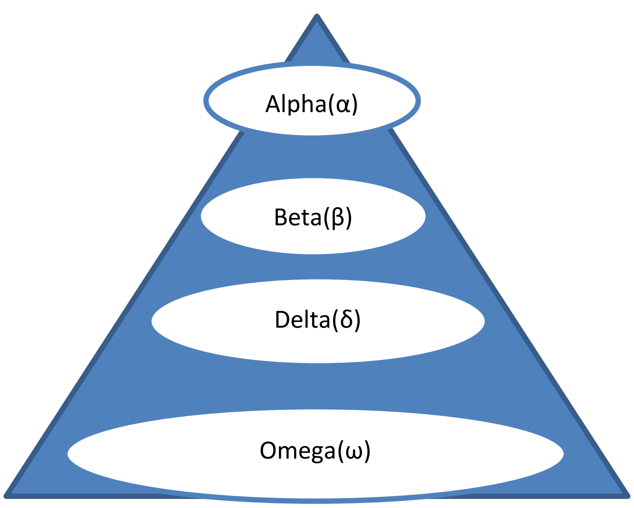


Figure 1. Leadership Social Hierarchy of Grey Wolf

During the hunting process, the alpha, beta, and delta wolves indicate the optimal location of prey and, accordingly, update the position of the pack's remaining wolves (omega). The hunting procedure is as follows:

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \quad (7)$$

Where X1, X2, and X3 are the positions of the prey according to alpha, beta, and delta grey wolf, respectively that is calculated as:

$$\overrightarrow{X1} = \overrightarrow{X\alpha} - \overrightarrow{A1} * (\overrightarrow{D\alpha});$$

$$\overrightarrow{X2} = \overrightarrow{X\beta} - \overrightarrow{A2} * (\overrightarrow{D\beta});$$

$$\overrightarrow{X3} = \overrightarrow{X\delta} - \overrightarrow{A3} * (\overrightarrow{D\delta}) \quad (8)$$

$D\alpha$, $D\beta$ and $D\delta$ are the distance between prey and alpha, beta, and delta grey wolf, respectively that is calculated as:

$$\overrightarrow{D\alpha} = \left|\overrightarrow{C1} * \overrightarrow{X\alpha} - \vec{X}\right|;$$

$$\overrightarrow{D\beta} = \left|\overrightarrow{C2} * \overrightarrow{X\beta} - \vec{X}\right|;$$

$$\overrightarrow{D\delta} = \left|\overrightarrow{C3} * \overrightarrow{X\delta} - \vec{X}\right| \quad (9)$$

Where $X\alpha$, $X\beta$ *and* $X\delta$ are the position of alpha, beta, and delta grey wolf, respectively? However, C1, C2, and C3 are the constant parameters.

4. Study Area and Methodology

A study area of 28× 28 km square that contain the Erbil city from Landsat_8 for March of 2021 was selected. The path and row number of the available frame is (169, 35) respectively, the projection is UTM the Datum and Ellipsoid is WGS84 and the UTM zone is 38. The quality of the data is (9 m) according to the Metadata file that was attached to the data set during the downloading the imagery from USGS website. The Landsat 8 contains 11 bands that captured by two sensors, the Operational Land Imager (OLI) sensor and the Thermal Infrared Sensor (TIRS). In this study the bands that collected by OLI sensor was used and they are bands (2, 3, 4 and 8) that are Red, Green, Blue and panchromatic bands. The (OLI) sensor provides seasonal coverage of the global landmass at a spatial resolution of 30 meters (visible, near-infrared(NIR), short wave infrared (SWIR)); 100 meters thermal and 15 meters (panchromatic) imagery. The size of the selected area through whole image is 1880 by 1856 pixels.

Figure (2) depicts a flowchart of the proposed approach. The standard IHS fused technique transforms a color image from RGB space to the IHS color space. Then the intensity (I) band that contains the spatial information is replaced by the panchromatic image. The result of the fusion is high spatial resolution and low spectral resolution [10]. There are different algorithms that have been used for calculating of (I), in this paper, I was calculated as equation (2).

In this study, the proposed method was compared with the standard IHS that proposed by other researchers, in this study the algorithm of standard IHS known as (nonlinear IHS triangle transform) was used that has a better result through other standard IHS algorithms and can be found in [18, 19].

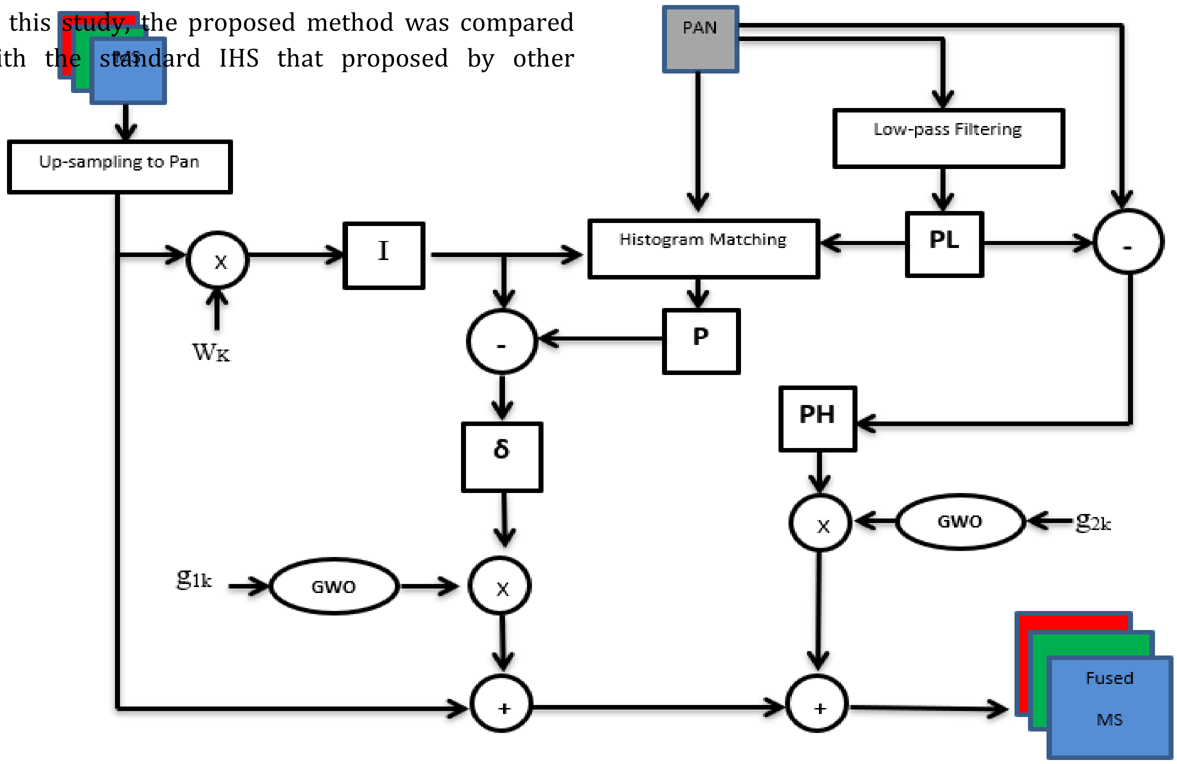


Figure 2. The proposed method's block diagram

For overcoming the spectral distortion, many researchers tried in this field as discussed previously in the study.

According to the other research, the procedure of our proposed method is as follows:

1. Before fusion, some preprocessing such as:
   a) Radiometric correction was done on the Landsat satellite images using ENVI 5.3 software, this type of correction without regarding the position and geometric properties of the image, will work only on the digital number (DN) of each pixel of image and try to correct value of each pixel.
   b) The multispectral image was up-sampled by a factor 2 by which the scale of both types of image are equal and normalizes the DN of images between [0 & 1] [10].
2. Computing the intensity component (I), using the more commonly mentioned algorithm in researches, as mentioned in equation (2)
3. Performing the low-pass filter for PAN image is required before histogram matching (next step) [5].
4. Using equation (4), histogram matches the PAN image to I component, to guarantee that the mean and standard deviation of the

panchromatic and multispectral images are within the same range.

5. Perform the high-pass filter for PAN image. This spatial filter emphasizes an image's detailed high-frequency components and deemphasizes the more general low-frequency information [20].
6. Using the GWO for deciding on injection gain weight for high-pass filter and the weight of MS bands that are divided by I component according to the equation (5 & 6), the ERGAS metric was used for selecting the optimal values through the objective function, its algorithm illustrated in equation(10).
7. Inject the extracted details according to equation (6).

$$ERGAS_{F,MS}=100\,\frac{H}{L}\sqrt{\frac{1}{n}\sum_{1}^{n}\frac{RMSE^2(Fi-MSi)}{Mi^2}} \qquad (10)$$

Where: F and MS are the fused and low-resolution MS images, H and L denote the resolutions of fused and MS images, and Mi. is the mean radiance of a unique band involved in the fusion.

The bellow table represents the initial setting for GWO:

Table 1. Initial setting for GWO

Number of wolf	8
Number of the iterations	50

There are several approaches for analyzing and evaluating the output of image fusion techniques. When comparing the various approaches, the spatial and spectral information was very noteworthy. It is simple to determine the sharpness of an edge when examining the quality of spatial information. However, while assessing the quality of spectral information, it is difficult to compare the colors of the result to the original multi-spectral information by using optical inspection. There are several criteria that assess the quality of spectral information. In this paper, more common quality assessments of spatial and spectral information, such as the Root Mean Square Error (RMSE), Signal to Noise Ratio (SNR), Correlation Coefficient (CC), Entropy (EN), Spatial Frequency (SF), and Average Grades (AG), were applied to the results of the proposed fusion algorithm.

5. Quality Assessment and Experimental Results

The relevance and growing use of the fused image must be assessed before being utilized for remote sensing applications. Several quality criteria are available to evaluate the performance of the fused image, including qualitative and quantitative analysis.

a.) **Qualitative Analysis:** One method for evaluating the merged image is qualitative analysis (visual analysis). Optical parameters including spatial details, geometric patterns, object size, color, and so on can be used for evaluation in this method. The benefit of visual analysis is that it is a straightforward, kind, and honest way to assess the quality of the fused image. However, it is dependent on the observers' experience and viewing conditions, which will create some ambiguity. Accurate mathematical models cannot represent qualitative assessment. In terms of color and spatial information, the fused image is compared to the original MS and PAN images.

b.) **Quantitative Analysis:** The quantitative evaluation of remote sensing image fusion is an effective method for determining the quality of the output images. Several ways and metrics can be objectively and automatically assessed. Hence, they may be classed as Full Reference techniques (FR) and No-Reference techniques (NR). The quality of a test image is evaluated in FR image quality assessment systems by comparing it to a reference image that is believed to be of perfect quality; Table (2) illustrates several metrics in this category. NR measures attempt to assess the quality of an image without reference to the original; Table (3) shows various metrics in this area.

Table 2. Evaluation metrics with the reference image.

MQ	Description	Algorithm	Reference

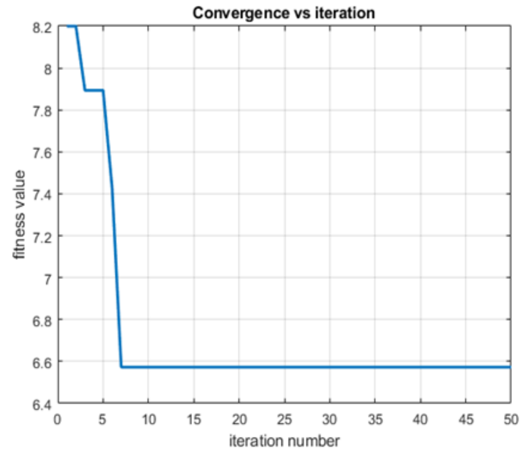
RMSE	Root Mean Square Error (RMSE) among each resampled MS band and the merged image quantifies the radiance changes of pixel values (DN). The ideal value is 0.	RMSE= $\sqrt{E(DNms - DNfused)}$	[21]
SNR	Signal to Noise Ratio (SNR), The signal is the information content of the data in the original MS image Mk. However, the merging Fk might generate noise as an error that is added to the signal.	$SNR_k = \sqrt{\frac{\sum_i^n \sum_j^m (Fk(i,j))^2}{\sum_i^n \sum_j^m (Fk(i,j) - Mk(i,j))^2}}$	[22]
CC	The Correlation Coefficient (CC) measures the closeness or similarity between two images. Its value is between -1 & +1, and the ideal value is +1.	$CC = \frac{\sum_i^n \sum_j^m (Fk(i,j) - \mu Fk)(Mk(i,j) - \mu Mk)}{\sqrt{\sum_i^n \sum_j^m (Fk(i,j) - \mu k)^2} * \sqrt{\sum_i^n \sum_j^m (Mk(i,j) - \mu k)^2}}$	[22]

Table 3. Evaluation metrics without reference image

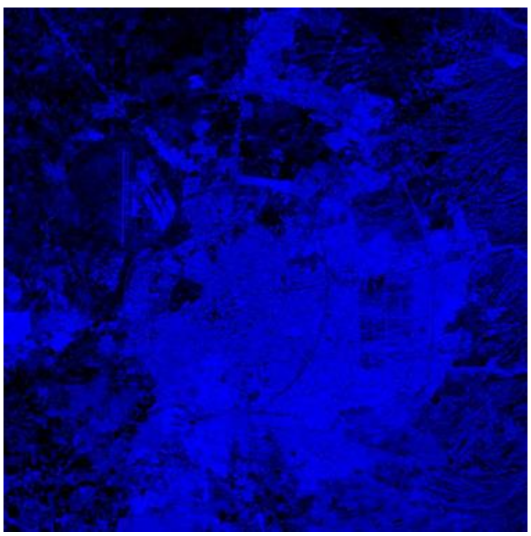
MQ	Description	Algorithm	Reference
EN	The entropy (En) of an Image measure of information content has not been utilized to analyze the consequences of information change in fused images. The large value indicates more information.	$En = -\sum_{i=0}^{255} P(i) log2\ P(i)$	[22]
SF	Spatial Frequency (SF) is calculated by the fused image's row frequency and column frequency. The higher the SF indicates that gray levels vary abruptly in image area and represent high spatial information.	$SF = \sqrt{RF^2 + CF^2}$	[15]
AG	Average Grades (AG) have been used to quantify image sharpness. The gradient at any pixel is the derivative of nearby pixels' DN values. A higher value represents a sharper image.	$AG = \frac{1}{(m-1)(n-1)} \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} \sqrt{\frac{\Delta Ix^2 + \Delta Iy^2}{2}}$ $\Delta Ix = f(i+1, j) - f(i,j)$ $\Delta Iy = f(i, j+1) - f(i,j)$	[22]

The application of the proposed algorithm and standard method on satellite image datasets are illustrated in Figure (3). The proposed method is compared with the standard IHS proposed by other researchers. In this study, the algorithm of standard IHS known as (the nonlinear IHS triangle transform) was used that has a better result than other standard IHS algorithms and can be found in [18, 19]. It can be noticed from standard IHS that there are some color distortions in the blue band of the fused image through incorrect spatial detail extraction and injection to the MS during the inverse RGB computation.

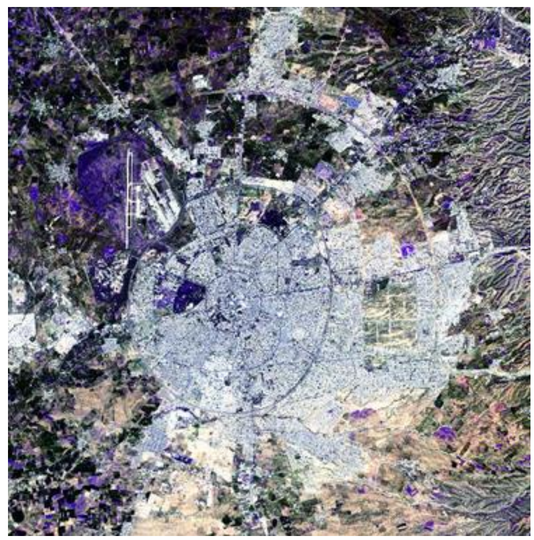
a



b



c



d

Figure 3. The fusion result: (a): Fused image based the proposed algorithm, (b): GWO iterations result for 50 iterations, (c): Color transform from RGB to IHS, (d): IHS standard image fusion

In Figure (4), the result of the fusion is represented for qualitatively understanding, that is a small cropped area (400 × 400 pixels) from the original results. The borders of roads, houses, and agricultural boundaries are plainly discernible in the selected zone, and spectral distortion is not visible in the output fused image.

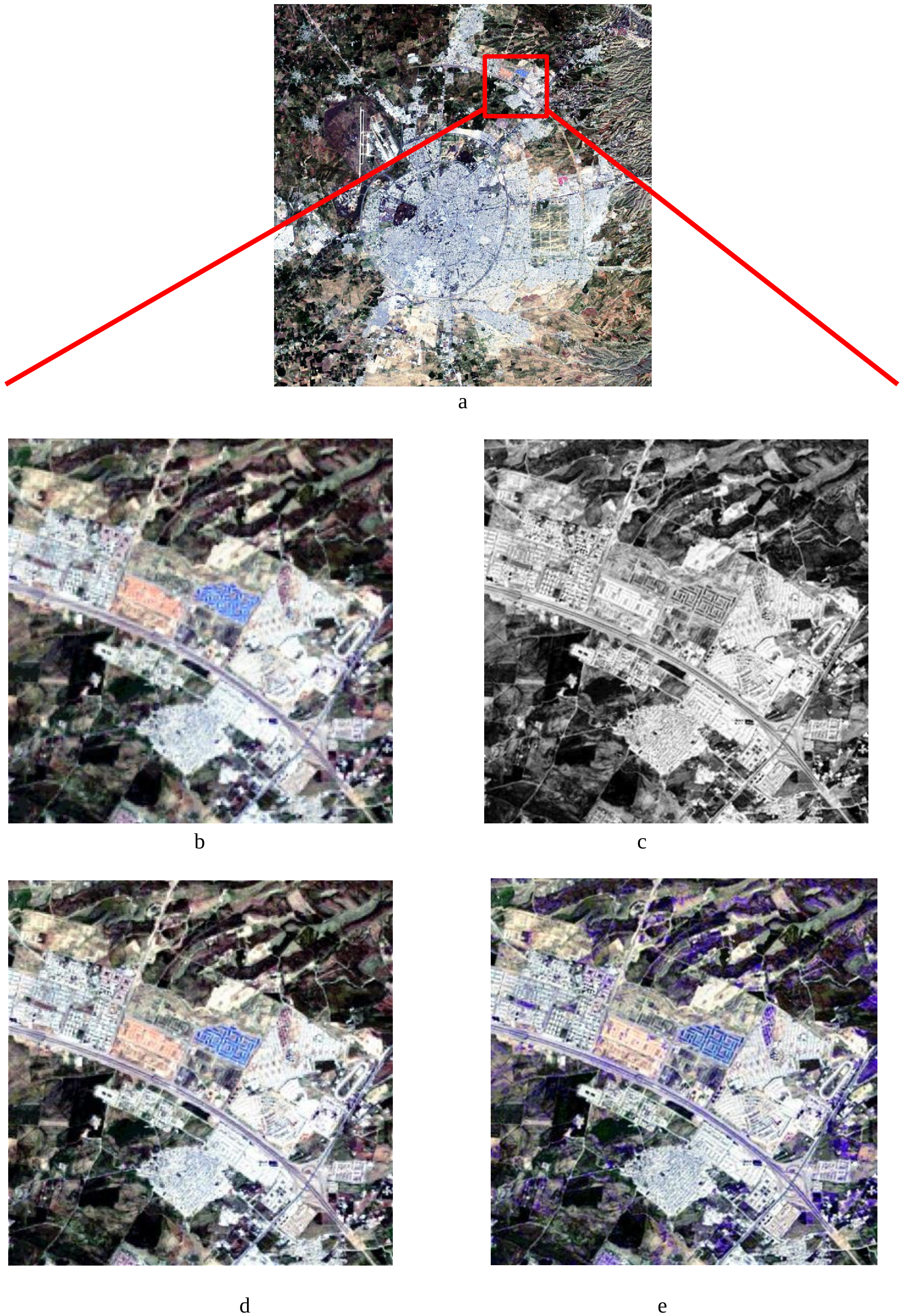


Figure 4. (a) The whole under study area, the fusion result: (b): The up-sampled MS with resolution of 30m, (c): The PAN image with resolution of 15m, (d): The fused image through the proposed algorithm, (e): IHS standard image fusion

The result of the proposed algorithm by using the GWO for finding the optimal weight of injection gain to the MS, the fitness values are illustrated in Table (4) and Figure 3(b) from the iteration number (7).

Table 4. The best cost and optimal gain weight using GWO

g_{1k}	g_{2k}	ERGAS
0.2015	0.5518	6.5729

The quantitative assessments are represented in the Tables (5 and 6), in the former one that is specify to the proposed method, the RMSE, SNR and En for all three bands are represent the better result in compare to the other table that illustrates the assessment of the standard method, also the cc in the blue band is more near to 1 and for the two other bands there is a little difference between the two methods. In the other hand, the SF and AG that response to represent the spatial quality is appeared better for the standard method but also there are small differences between the two methods, and some of these different and better results by existed methods expected to be because of the color distortions.

Table 5. Evaluation metrics for optimized IHS

Band NO	RMSE	SNR	CC
R	16.681	37.973	0.97684
G	16.875	37.732	0.97778
B	17.105	37.519	0.98042
Band NO	En	SF	AG
R	9.4761	45.185	23.303
G	9.5065	44.661	23.062
B	9.4563	42.02	21.848

Table 6. Evaluation metrics for standard IHS

Band NO	RMSE	SNR	CC
R	27.565	29.247	0.99117
G	28.82	28.434	0.98908
B	36.614	24.298	0.94538
Band NO	En	SF	AG
R	6.3895	46.848	24.289
G	6.4003	48.257	25.463
B	6.4312	52.162	27.506

6. Conclusion

A new IHS algorithm for image fusion is proposed based on other existing algorithms to overcome and degrade the existing spectral distortions by using the standard fusion methods. The general idea is to find the optimal injection gain for spatial details that must be injected into the low-resolution MS image using the GWO optimization algorithm based on an objective function for minimizing the ERGAS metric. To estimate the assessment of the result, both qualitative and quantitative metrics of the assessment are used, depends on these metrics, the proposed algorithm gets a better result in compare to the standard existing methods, as In qualitative evaluation that is based on visual analysis, in the selected zones the edges of roads, buildings and boundary of agricultural areas can be sense easily and the spectral distortion cannot be seen in the output fused image, the mean result of the FR technique of quantitative metrics respectively were as follow: (***16.8870, 37.7413 and 0.9783***) as well as the mean result of NR technique for the proposed method respectively were as follow: (***9.4796,***

43.9553 and 22.7377). Increasing and changing the objective functions through optimization algorithm in the next study, can be used to increase the quality of the image fusion.

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