Increase the Intelligibility of Multispectral Image Using Pan-Sharpening Techniques for Many Remotely Sensed Images

Israa J.M. Al-Rubiey
Dept. of Physics, College of Science, University of Baghdad

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Abstract

Pan sharpening (fusion image) is the procedure of merging suitable information from two or more images into a single image. The image fusion techniques allow the combination of different information sources to improve the quality of image and increase its utility for a particular application. In this research, six pan-sharpening method have been implemented between the panchromatic and multispectral images, these methods include Ehlers, color normalize, Gram-Schmidt, local mean and variance matching, Daubechies of rank two and Symlets of rank four wavelet transform. Two images captured by two different sensors such as landsat-8 and world view-2 have been adopted to achieve the fusion purpose. Different fidelity metric like MSE, RMSE, PSNR, Cc, ERGAS and RASE have been used to achieve the comparison among the fusion methods. The results show that Daubechies wavelet (db2) transform was good method for pan sharpening images. Where good statistical values have been obtained, when it is applied on the first and second image that are captured by different sensors with different spatial resolution.

Keyword: Images pan sharpening, Ehlers, Gram-Schmidt, wavelet, local variance matching.

Introduction

Pan-sharpening or fusion is defined as the process of combining substantial information from several sensors using mathematical techniques in order to create a single composite image that will be more comprehensive and thus, more useful for a human operator or other computer vision tasks. Image fusion provides an effective way of reducing this increasing volume of information by extracting all the useful information from the source images. It provides an effective method to enable comparison and analysis of Multi-sensor data having complementary information about the concerned region [1, 2]. Image fusion takes place at three different levels i.e. pixel, feature and decision. Pixel level is a low level of fusion, which is used to analyze and combine data from different sources before original information is estimated and recognized. Feature level is a middle level of fusion, which extracts important features from an image like shape, length, edges, segments and direction. Decision level is a high level of fusion that points to actual target [3]. Most optical remote sensing satellites carry two types of sensors – the panchromatic and the multispectral sensors. The multispectral sensor records signals in narrow bands over a wide instantaneous field of view (IFOV) while the panchromatic sensor records signals over a narrower IFOV and over a broad range of the spectrum. Thus, the multispectral (MS) bands have a higher spectral resolution, but a lower spatial resolution compared to the associated panchromatic (PAN) band, which has a higher spatial resolution and a lower spectral resolution. Before applying pan sharpening methods between the images, these images must be registered and resized, where the registration is the process of geometrically aligning two or more images of the same scene acquired at different times, or with different sensors, or from different viewpoints [4]. It is one of the crucial image processing operations in remote sensing. In this research, different pan sharpening methods have been adopted such as Ehlers, color normalize, Gram-Schmidt, local mean and variance matching, Daubechies and symlet wavelet transform. As well as many fidelity criteria have been used for results evaluation.

Studied Area and Variable Data

In this research, two set of image have been used to perform the pan sharpening methods between them, the first image was captured by Landsat -8. Geographically, its apart of Baghdad city capital of Iraq, located between longitude (432637.5 m - 438577.5 m) E and latitude (3712147.5 m - 3706192.5 m) N table (1) lists the spectral and spatial resolutions of the Landsat-8 ETM+ sensor [5]. The second image is captured by worldview-2. Geographically, it's a part of Alabama state in southeastern of the united states, located between longitude (335635.5 m -335832.00 m) E and latitude (6250443.5 m - 6250245.000 m)N. Table (2) gives the same information for the wordview-2 sensor [6]. The Landsat-8 Multispectral bands have a spatial resolution of 30 m while the panchromatic band has a 15 m resolution, the word view-2 have 2m spatial resolution for Multispectral bands and 0.5m for panchromatic band. The first and second image can be shown in figure (1 & 2) respectively.

Image registration

Image registration of different images has been done to make the image unified to same coordinate system. Registration is used to establish a spatial correspondence between the sensor images and to determine a spatial geometric transformation, called warping, which aligns the images. Registration techniques align the images by exploiting the similarities between sensor images. The mismatch of image features in multispectral images reduces the similarities between the images and makes it difficult to establish the correspondence between the images [7]. In this research the nearest neighbor interpolation method has been adopted to resize and register the multispectral image to be the same size pixel of the panchromatic image pixel.

Pan sharpening methods

This section describes some pan sharpening algorithms implemented in practice along with their properties. Image fusion methods that can be used for high-resolution satellite image fusion have been reviewed and analyzed, such as those for fusion of panchromatic and multi-spectral images:

1. Ehlers transform

The Ehlers fusion is based on an IHS transform coupled with a Fourier domain filtering. This technique is extended to include more than 3 bands by using multiple IHS transforms until the number of bands is exhausted. A subsequent Fourier transform of the intensity component and the panchromatic image allows an adaptive filter design in the frequency domain [8]. The basic idea behind this method is to modify the input pan image to look more like the intensity component [9]. In the first step in order to manipulate HIS components, three low resolution multispectral RGB bands are selected and transformed into the IHS domain. Then, the intensity component and the panchromatic image are transformed into the spectral domain via a two-dimensional Fast Fourier Transform (FFT). Low pass (LP) and high pass (HP) filter were directly performed in the frequency domain on the intensity component and the high resolution panchromatic image respectively [10]. The idea is to replace the high frequency part of the intensity component with that from the Pan image. To return both components back into the spatial domain an inverse FFT transform was used. Then the high pass filtered panchromatic band and low pass filtered intensity are added and matched to the original intensity histogram. Finally, an inverse IHS transform converts the fused image back into the RGB color domain to obtain the high resolution multispectral image [11].

2.Color Normalize

Color normalized sharpening technique used a mathematical combination of the color image and high resolution image. Each band in the color image is multiplied by a ratio of the high resolution data image divided by the sum of the color bands. The nearest neighbor interpolation has been used for re-sampling of the three color bands to the high-resolution pixel size. The output RGB images will have the pixel size of the input high-resolution data. The CN transform is defined by the following equation [12]:

$$CN_i = \frac{3*(MS_i+1)*(PAN+1)}{\sum_i MS_i+3} - 1 \text{ ---------------------- } (1)$$

Where MS is multispectral image, PAN is panchromatic image and CN_i, is the output color normalized band.

3.The Gram-Schmidt pan-sharpening method

Pan-sharpening algorithms are used to sharpen multispectral data using high spatial resolution panchromatic data. An underlying assumption of these algorithms is that you can accurately estimate what the panchromatic data would look like using lower spatial resolution multispectral data. Gram-Schmidt is typically more accurate because it uses the spectral response function of a given sensor to estimate what the panchromatic data. The low spatial resolution spectral bands are used to simulate the panchromatic band must fall in the range of the high spatial resolution panchromatic band or they will not be included in the resampling process [13, 14]

Step one: Simulating a panchromatic band from the lower spatial resolution spectral bands.

$$pan_{sim} = \sum_{k=1}^{n} W_k MS_k \text{ -------------------------- } (2)$$

Where W_k is the weight of pixel and MS_k is the multi-spectral image.

Step two: Performing a Gram-Schmidt transformation on the simulated panchromatic band, as the first band and the spectral bands.

Step three: Replacing the high spatial resolution panchromatic band with the first Gram-Schmidt band.

Step four: Applying the inverse Gram-Schmidt transform to form the pan-sharpened spectral bands.

4.Local mean and variance matching

The local mean and variance matching (LMVM) filter applies a normalization function at a local scale within the images in order to match the local mean and variance values of the high resolution panchromatic image with those of the original low resolution spectral channel. The small residual differences remaining correspond to the high spatial information stemming from the high resolution panchromatic image. This type of filtering fusion of Earth image data drastically increases the correlation between the fused product and the low resolution channel. The local mean and variance matching filter is given by [15]:

$$F_{i,j} = \frac{(H_{i,j} - \bar{H}_{i,j(w,h)}).\sigma(L)_{i,j(w,h)}}{\sigma(H)_{i,j(w,h)}} + \bar{L}_{i,j(w,h)} \text{ -------------- (3)}$$

where Fi,j is the fused image at pixel coordinates i, j, $H_{i,j}$ is the high spatial resolution image at pixel coordinates i, j, $\bar{L}_{i,j(w,h)}$ is the local mean of the low spatial resolution image calculated inside the window of size (w, h) at pixel coordinates i, j, $\bar{H}_{i,j(w,h)}$ is the local means of the high spatial resolution image calculated inside the window of size (w, h) at pixel coordinates i, j, $\sigma(L)_{i,j(w,h)}$ is the local standard deviation of the low spatial resolution image calculated inside the window of size (w, h) at pixel coordinates i, j, and $\sigma(H)_{i,j(w,h)}$ is the local standard deviation of the high spatial resolution image calculated inside the window of size (w, h) at pixel coordinates i, j [16,17].

5.Daubechies and Symlets wavelet transform

Discrete wavelet transforms a discrete time signal into a discrete wavelet representation. In the case of DWT, there is a time-scale representation of the digital signal which is obtained using digital filtering techniques. The signal to be analyzed here is passed through filters with different cutoff frequencies at different scales [18]. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal is passed through two complementary filters and emerges as two signals, approximation and details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis see figure (3). The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform. The wavelet transforms W of the two registered input images $I_1(x, y)$ and $I_2(x, y)$ are computed and these transforms are combined using some kind of fusion rule φ Then the inverse wavelet transform w^{-1} is computed and the fused image $I(x, y)$ is reconstructed, see below equation [19]:

$$I(x,y) = w^{-1}(\varphi\ (w(I_1(x,y), w\left(I_2(x,y)\right) \text{ --------- (4)}$$

In this research, two wavelet models of wavelet families have been used Symlets and Daubechies wavelets. The Symlets were proposed as modifications to the Daubechies family with the difference that whereas the Daubechies wavelets have maximal phase, the Symlets have minimal phase. The Symlets are designed so that they have the least asymmetry and maximum number of vanishing moments for a given compact support [18]. The Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. The Daubechies wavelet (db2) decomposed up to five levels has been used here for image fusion. These wavelets are used here because they are real and continuous in nature and have least root-mean-square (RMS) error compared to other wavelets [20, 21]. The steps of the wavelet based image fusion are explained as follows:

Step 1: Register and resize the low resolution image to be the same size of high resolution panchromatic image using nearest neighbor interpolation.
Step 2: Read the two registration images.
Step3: Apply wavelet decomposition on both the images using (Daubechies or Symlet) filter.
Step 3: Extracts from the wavelet decomposition structure the horizontal, vertical, or diagonal detail.
Step 4: Perform average of approximation coefficients of both decomposed images
Step 5: Compare horizontal, vertical and diagonal coefficient of both the images and apply maximum selection Scheme to select the maximum coefficient value by comparing the coefficient of the two images. Perform this for all the pixel values of image.
Step 6: The inverse wavelet transform is then applied to the combined coefficient map to produce the fused image
Step 7: Display the final fused image.

Image Quality Metrics

The metrics are used to evaluate and for comparing the value of fused image and the original image. The different metrics are defined here which can be used for the evaluation of the image quality:

1.Mean square Error (MSE): The mathematic equation of MSE is given by:

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(ref_{ij} - fus_{ij}\right)^2 \text{ --------------- } (5)$$

Where *ref* is the reference image, *fus* is the fused image, *ij* row and column pixels, *mn* number of row and column pixels [22].

2.Root Mean Square Error (RMSE): A commonly used reference based assessment metric is the Root Mean Square Error (RMSE). The RMSE between a reference image (*ref*) and a fused image (*fus*) is given by the following equation [19]:

$$RMSE = [\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(ref(i,j) - fus(i,j))^2]^{1/2} \text{--- } (6)$$

Where $ref(i,j)$ and $fus(i,j)$are the reference and fused images, respectively, M and N are image dimensions. Smaller the value of the *RMSE*, better the performance of the fusion algorithm.

3.PEAK SIGNAL TO NOISE RATIO (PSNR): PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR of the fusion result is defined as follows [19]:

$$PSNR = 10\, log(\frac{(fus_{max})^2}{(RMSE)^2}) \text{ -------------------------------- } (7)$$

Where fus_{max} is the maximum gray scale value of the pixels in the fused image. Higher the value of the *PSNR*, better the Performance of the fusion algorithm.

4.Correlation Coefficient (Cc): The correlation coefficient measures the closeness or similarity in small size structures between the original and the fused images. It can vary between (-1 and +1). Values close to +1 indicate that they are highly similar while the values close to -1 indicate that they are highly dissimilar [23].

$$Cc = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}(Ms_{i,j}-\overline{MS})(fus_{i,j}-\overline{fus})}{[\sum_{i=1}^{N}\sum_{j=1}^{N}(Ms_{i,j}-\overline{MS})^2\sum_{i=1}^{N}\sum_{j=1}^{N}(fus_{i,j}-\overline{fus})^2]^{1/2}} \text{ --------- (8)}$$

Ms and $\overline{MS}$ are the value and mean value of multispectral, fus and $\overline{fus}$ is the value and mean value of fused image, ij are coordinates pixel values.

5.ERGAS: Which means relative dimensionless global error in synthesis. Is the normalized average error of each band. The ERGAS index for the fusion is expressed as follows:

$$ERGAS = 100\frac{h}{l}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{RMSE(B_i)^2}{(\overline{M_i})^2}} \text{ -------------------------- (9)}$$

Where N is the number of bands involved in fusion, h / l is the ratio of the spatial resolution of

Original Pan and MS images. $\overline{M_\iota}$ Is the mean value for the original spectral image B_I [24].

6.Relative Average Spectral Error (RASE): The relative average spectral error is a metric which monotonically depends on the RMSE in each band. It is given by:

$$RASE = \frac{100}{M}\sqrt{\frac{1}{N}\sum_{i=1}^{N}RMSE^2(B_i)} \text{ ----------------------- (10)}$$

Where M is the mean radiance of the N spectral bands (B_i) of the original MS bands [24].

Result, Discussion and Conclusions

Image pan sharpening techniques are originally devised to allow integration of different information sources, may take advantages of the complementary spatial and spectral resolution characteristics typical of remote-sensing imagery. In this research six pan sharpening method have been applied on two types of image. The first image (Baghdad city) captured by landsat-8 with spatial resolution 15 m and 30 m for panchromatic and multispectral bands respectively. The second image (Alabama State) captured by world view - 2 with spatial resolution 0.5 m and 2 m for panchromatic and multispectral image respectively. The metric quality measures on the difference between the original and synthesized images for the first image are presented in table (3). Subjectively, the results of Ehlers, color normalize, Gram-Schmidt methods give high quality and more clarity than local variance and wavelet transform which can be shown in figure (4). But objectively, the statistical results of the Gram-Schmidt and Daubechies (db2) wavelet give better results than the other pan sharpening methods, approximately, both Gram-Schmidt and Daubechies wavelet gave low value of (RMSE), high value of (Cc), low value of (ERGAS) and suitable value of (RASE). In general, there is a rate of similarity of the all fusion methods quality metric which applied on the first image.

This similarity of results belongs to that the spatial resolution of the panchromatic band of the first image is larger twice than the spatial resolution of the multispectral bands.

In the other hand, the quality metric of the pan sharpening methods for the second image, which can be seen in table (4), have a high quality metric such as (MSE), (RMSE), and (ERGAS) for Ehlers, color normalize and Gram- Schmidt methods, as be shown in figure (5). On the contrary, the good statistical measures such as (PSNR) and (Cc) can be noticed, when the local mean and variance matching, Daubechies wavelet (db2), and Symlets wavelet (sym4) fusion methods have been used. In general, there is a simple difference between the values of the quality metric of the all applied fusion techniques on the second image, due to that the spatial resolution of the panchromatic band of the second image is larger 4 times than the spatial resolution of the multispectral bands. A another important notice can be conclude from the tables No.(3) and No.(4) is that the mean square error (MSE) of fusing image using Ehlers, color normalize, Gram-Schmidt and local mean and variance matching of the image captured by word view-2 is large compared with the mean square error of the same fusion methods applied on image captured by landsat-8. Finally, the most important conclusion that can be recommended in this research was the Daubechies wavelet (db2) transform considered to be good method for pan sharpening images. The good statistical values have been obtained, when its applied on the first and second image that captured by different sensors with different spatial resolutions.

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Table (1): The characteristic of Landsat -8 bands [5]

Band	Wavelength (μm)	Resolution (m)
Band1-Coastal Aerosol	0.43-0.45	30
Band2- Blue	0.45-0.51	30
Band3- green	0.53-0.59	30
Band4-Red	0.64-0.67	30
Band5- NIR	0.85-0.88	30
Band6-SWIR1	1.57-1.65	30
Band7-SWIR2	2.11-2.29	30
Band8-panchromatic	0.50-0.68	15
Band9-Cirrus	1.36-1.38	30
Band10- TIRS1	10.60-11.19	100
Band11-TIRS2	11.50-12.51	100

Table (2): The spectrum of the Worldview-2 bands [6]

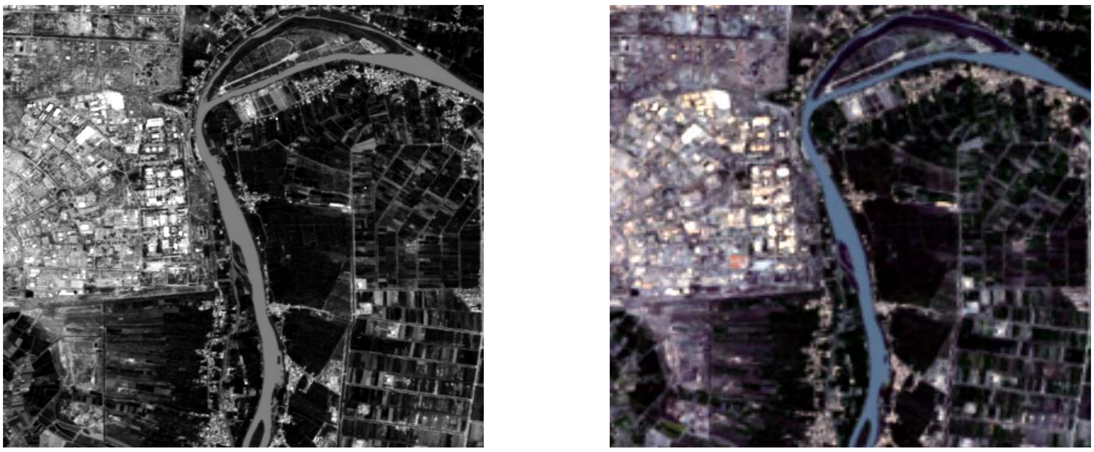
Band name	Center wavelength (nm)	Min. Lower band edge(nm)	mix. Upper band edge(nm)
panchromatic	632	464	801
Coastal	427	401	453
Blue	478	447	508
Green	546	511	581
Yellow	608	588	627
Red	659	629	689
Red edge	742	704	744
NIR1	831	772	890
NIR2	908	862	954

Table(3): The quality metric of the first image (Baghdad city) captured by landsat-8

	MSE	RMSE	PSNR	Cc	ERGAS	RASE
Ehlers	33.374	5.777	32.896	0.9313	1.652	15.825
Color normalize	39.368	6.274	32.179	0.926	1.904	15.07
Gram-Schmidt	22.414	4.713	34.664	0.944	1.359	16.308
Local mean and variance matching	49.185	7.013	31.212	0.966	2.514	9.235
Daubechies wavelet (db2)	31.871	5.645	33.096	0.984	1.988	8.052
Symlets wavelet (sym4)	46.451	6.815	31.460	0.956	2.337	11.346

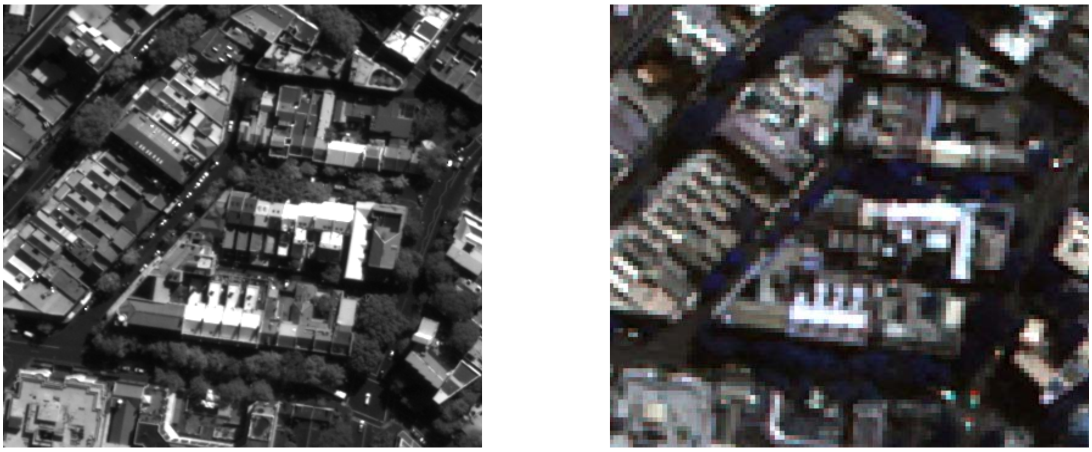
Table. (4): The quality metric of the second image(Alabama state) captured by world view-2

	MSE	RMSE	PSNR	Cc	ERGAS	RASE
Ehlers	59.994	7.745	30.349	0.890	2.359	15.271
Color normalize	63.378	8.085	29.976	0.887	2.728	13.095
Gram-Schmidt	75.292	8.671	29.363	0.891	3.076	12.170
Local mean and variance matching	42.47	6.517	31.849	0.96	2.330	8.8109
Daubechies wavelet (db2)	32.938	5.739	32.953	0.964	1.953	11.315
Symlets wavelet (sym4)	43.133	6.567	31.782	0.923	2.119	13.704



a- Panchromatic image (15 m) b- multispectral image (30 m)

Figure(1): The panchromatic and multispectral of Baghdad image captured by landsat-8



a- Panchromatic image (0.5 m) b- multispectral image (2 m)

Figure. (2):The panchromatic and multispectral of Alabama state captured by worldview-2

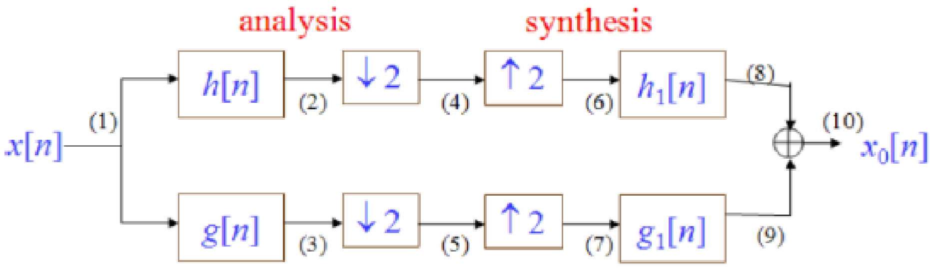
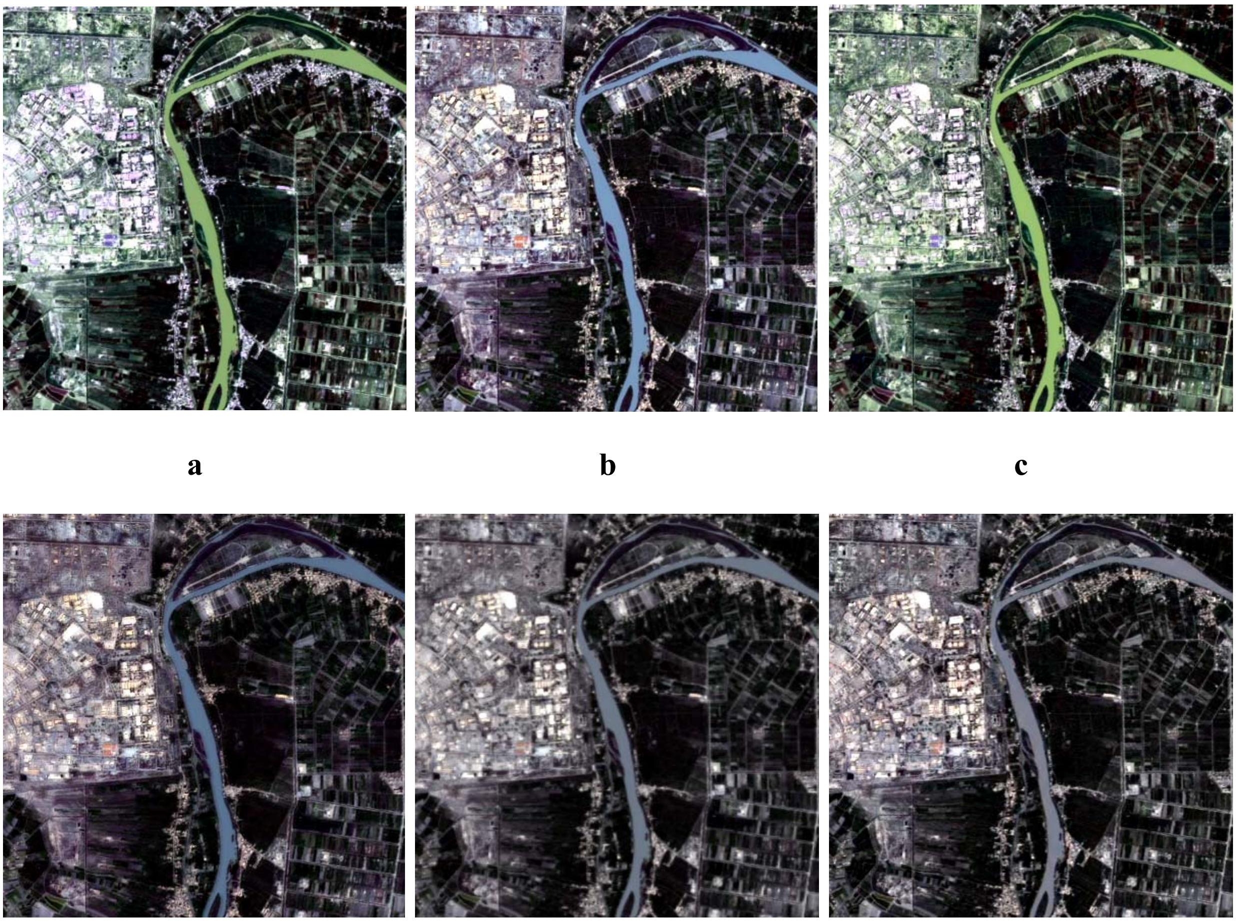


Figure (3): Process of wavelet transform [19]



a   b   c

d   e   f

Figure (4): Results fused image of the first image captured by landsat-8 using a) Ehlers, b) color normalize, c) Gram-Schmidt, d) local mean and variance matching, e) Daubechies wavelet, and f) Symlets wavelet

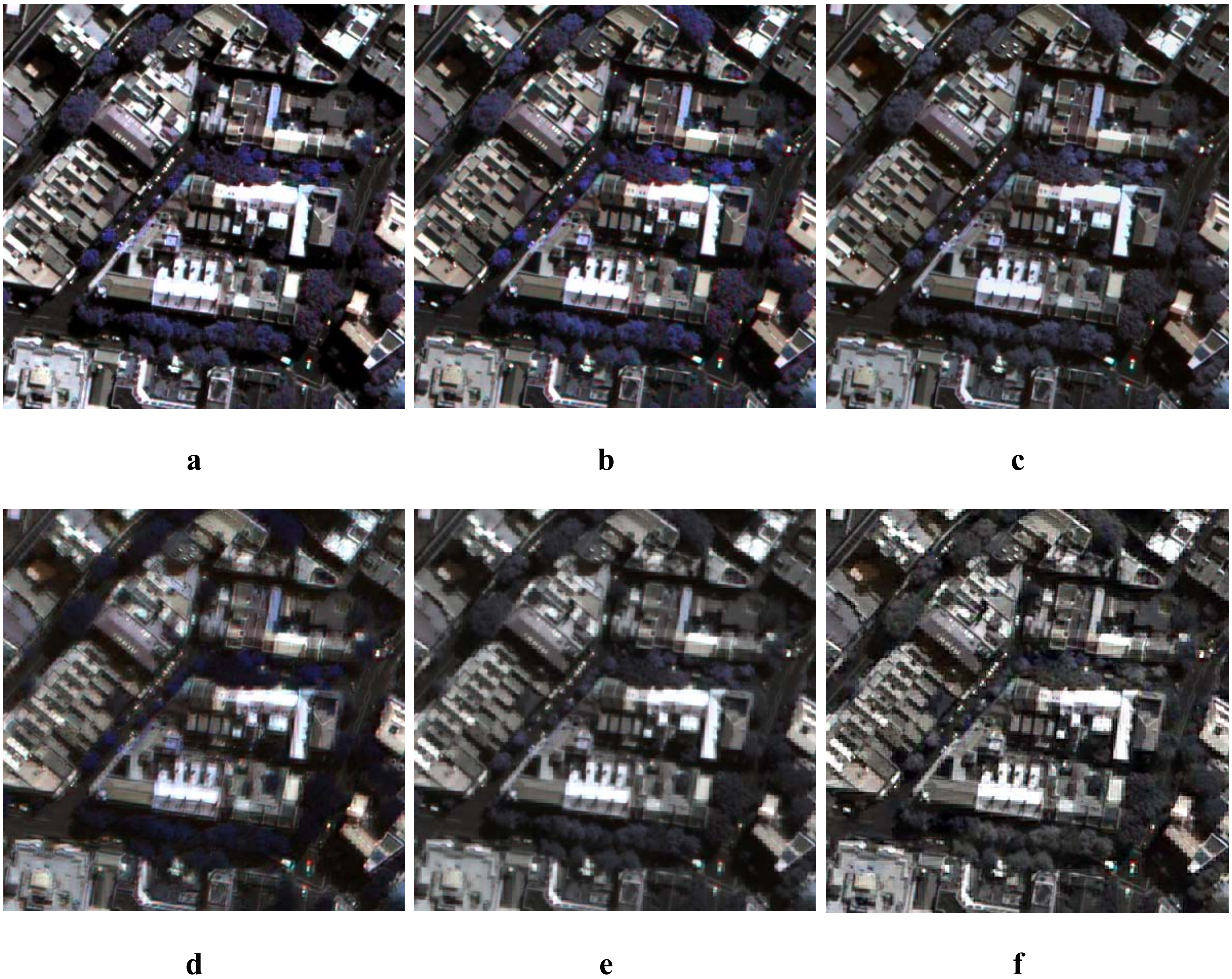


Figure (5) :Results fused image of the second image captured by world view-2 using a) Ehlers, b) color normalize, c) Gram-Schmidt, d) local mean and variance matching, e) Daubechies wavelet, and f) Symlets wavelet

زيادة وضوح الصورة المتعددة الحزم بإستعمال تقانات زيادة الحدة (الدمج) لعدد من الصور الفضائية

اسراء جميل محسن الربيعي
قسم الفيزياء/ كلية العلوم/ جامعة بغداد

استلم في:7تشرين الأول 2015، قبل في : 15تشرين الثاني 2015

الخلاصة

زيادة الحدة (دمج الصور) هي عملية تركيب المعلومات المناسبة من صورتين أو أكثر للحصول على صورة منفردة. ان تقنيات دمج الصور تسمح بتركيب معلومات من مصادر مختلفة وذلك لتحسن كفاءة الصورة وزيادة فائدتها للتطبيقات العملية. في هذا البحث تم تطبيق ست تقنيات لدمج الصورة المتعددة الحزم مع الصورة الأحادية الحزمة، وتشمل هذه التقنيات على Ehlers, color normalize, Gram-Schmidt, local mean and variance matching, Daubechies wavelet, symlet wavelet. تم استعمال نوعين من الصور الأولى تم التقاطها بوساطة القمر الصناعي landsat-8 والثانية تم التقاطها بوساطة القمر الصناعي world view-2 كما تم اعتماد معايير دقة مختلفة مثل MSE, RMSE, PSNR, Cc, ERGAS, RASE وذلك لتقييم الصور الناتجة. تظهر النتائج طريقة التحويل المويجي Daubechies هي افضل طريقة لدمج الصور الفضائية، إذ تم الحصول على معايير دقة عالية عندما طبقت هذه الطريقة على انواع من الصور ملتقطة بمتحسسات فضائية مختلفة الدقة الحيزية.

الكلمات المفتاحية: زيادة الحدة (دمج الصور)، Ehlers، Gram-Schmidt، تحويل wavelet، مطابقة التغاير المحدد.