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Multispectral and Panchromatic Image Fusion using Empirical Wavelet Transform

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Abstract

Pan sharpening is the process of fusion of panchromatic and multispectral image to obtain an output image of high spatial and spectral resolution. It is very important for various remote sensing applications such as image segmentation studies, image classification, temporal change detection etc. The present work demonstrates the application of Empirical Wavelet Transform for the fusion of panchromatic image and multispectral image by simple average fusion rule. The Proposed method is experimented on panchromatic and multispectral images captured by high resolution earth observation satellites such as GeoEye-1, QuickBird, WorldView-2 and World View-3. The effectiveness of our proposed method is evaluated by visual perception and quantitative assessment measures. The experimental analysis shows that the proposed method performs comparable to the existing fusion algorithms such as Multi-resolution Singular Value Decomposition and Discrete Wavelet Transform.

Keywords: Discrete Wavelet Transform, Empirical Wavelet Transform, Image Fusion, Multi-resolution Singular Value Decomposition, Pan sharpening, Quality metrics

1. Introduction

Pan sharpening is the technique of fusing panchromatic image and multispectral image to obtain a fused output image of high spatial and spectral resolution[1]. A multispectral image contains more than one spectral band. It contains a higher degree of spectral resolution. Unlike multispectral image, panchromatic images are single band images collected over a wide range of visible spectrum. Spatial resolution of panchromatic images is high when compared to multispectral images. Visual exploitation and simple visual image interpretation of the multispectral images are enhanced by increasing the spatial resolution of high spectral resolution multispectral image. There are number of methods available in literature for pan sharpening[2].

Spatial domain and Transform domain fusion methods are the two groups of image fusion techniques[3]. Source image is primarily transferred into frequency domain in the case of transform domain fusion method whereas, Spatial domain fusion method directly deals with the pixels of source images.

Discrete Wavelet Transform (DWT), Multi-resolution Singular Value Decomposition (MSVD) based image fusion methods etc are the some of the popular transform domain image fusion techniques.

With the advent of multi resolution analysis in image processing, wavelet transform has become an effective tool in

Image fusion. The fusion method using wavelet transform decomposes the panchromatic image and the multispectral image from which, the approximation coefficients of the multispectral band and the detail coefficients of the panchromatic image are considered to reconstruct a band[4]. This decomposition is repeated further, to increase the frequency resolution. After decomposition, the approximation components

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and detail components can be separated. Finally, the output image is obtained using inverse wavelet transform[5]. It is found that the wavelet based fusion techniques reduces color distortion and provides better quality fused image with enhanced spatial and spectral resolution[6].

Multi-resolution Singular Value Decomposition is similar to wavelet transform where, signal is filtered by high pass and low pass finite impulse response filters separately[7,8]. The output of each filters are down sampled to achieve first level decomposition. This process is further repeated for the down sampled output of low pass filter to achieve the second level decomposition. By repeating the same procedure, successive decomposition levels can be achieved. In Multi-resolution Singular Value Decomposition, the finite impulse response filters are replaced with Singular Value Decomposition (SVD). MSVD decomposes the input images to several levels. The fusion rule selects the larger absolute value of the two MSVD detailed coefficients at each level of decomposition[9]. Also the approximation coefficients at coarser level are smoothed and sub sampled version of original image[9]. In this approach, the fusion rule takes the average of MSVD approximation coefficients at coarser level. Likewise, at each decomposition level, fusion rule takes the average of two MSVD Eigen matrices[10].

In this paper, we focus on Empirical Wavelet Transform (EWT) based image fusion scheme to fuse high spatial resolution panchromatic image with high spectral resolution multispectral image. The result obtained by our proposed method is compared with other existing techniques namely Discrete Wavelet Transform and Multi-resolution Singular Value Decomposition based image fusion techniques.

The remaining article is organized as follows. Section II gives the mathematical background of Empirical Wavelet Transform whereas; section III contains the description of EWT based fusion method. Section IV gives the experimental analysis of proposed method. Finally Section V concludes the paper.

2. Overview of Empirical Wavelet Transform

Empirical Wavelet Transform (EWT) can be explained as the combination of wavelets formalism and the adaptability of Empirical Mode Decomposition (EMD). Wavelets and their geometric extensions are very efficient in image processing. The Empirical Wavelet Transform (EWT) decomposes a signal or an image on wavelet tight frames which are built adaptively. The key advantage of this empirical approach is to keep together some information that should be separated in the case of dyadic filters. This property of Empirical Wavelet Transform is used in image fusion to improve the quality of fused image.

In Empirical Wavelet Transform, a set of wavelets are build by adaption from the processed signal. The main idea behind EWT is to extract different modes of a signal by designing appropriate wavelet filter banks. This algorithm was first proposed by Jerome Gilles in[11]. The similar approach is used in the Fourier method of forming band pass filters. For the adaption process, the location of information in the spectrum is identified with frequency, $\omega \in [0, \pi]$. This is used to make the support of the filter. Initially, the Fourier transformed signal is partitioned into N segments. Each segments will have the boundary limits denoted as ω_n[11].

Each partition is denoted as $\wedge_n = [\omega_{n-1}, \omega_n]$, $\bigcup_{n=1}^{N} \wedge_n$. Around each ω_n, a small area of width $2\tau_n$ is defined. This denotes a transition phase. The empirical wavelets are defined on each of the $\wedge_n$. It is a band-pass filter constructed using Littlewood-Paley and Mayer's wavelets[11]. The sub bands are extracted through these filtering operations.

Each partition in the spectrum is considered as modes which contains a central frequency with certain supports. If there are N partitions, there will be N + 1 boundary limits. Since 0 and π are used as the limits to the spectrum, the number of boundary limits required will be (N-1)[11,12]. The boundaries are calculated by the following two steps:

- Finding local maxima in the spectrum.
- Sorting it in the decreasing order by excluding and selecting the M boundary values.

Therefore the partition boundaries, ω_n, comprises of 0, selected maxima and π.

Two possibilities for the selection of the boundaries:

- $M \geq N$
- $M \leq N$

The expression for scaling and empirical wavelet functions are defined as,

$$\hat{\phi}_n(\omega) = \begin{cases} 1 & if \quad |\omega| \leq \omega_n - \tau_n \\ \cos[\frac{\pi}{2}\beta(|\omega| - \omega_n + \tau_n)] & \\ & if \quad \omega_n - \tau_n \leq |\omega| \leq \omega_n + \tau_n \\ 0 & otherwise \end{cases}$$

$$\hat{\psi}_n(\omega)=\begin{cases}1 & if\ \ \omega_n+\tau_n\le|\omega|\le\omega_{n+1}-\tau_{n+1}\\ \cos[\frac{\pi}{2}\beta(\frac{1}{2\tau_{n+1}}(|\omega|-\omega_{n+1}+\tau_{n+1}))] & \\ & if\ \ \omega_{n+1}-\tau_{n+1}\le|\omega|\le\omega_{n+1}+\tau_{n+1}\\ \sin[\frac{\pi}{2}\beta(\frac{1}{2\tau_n}(|\omega|-\omega_n+\tau_n))] & \\ & if\ \ \omega_n-\tau_n\le|\omega|\le\omega_n+\tau_n\\ 0 & otherwise\end{cases}$$

The function $\beta(x)$ is an arbitrary function defined as,

$$\beta(x)=\begin{cases}0 & if\ \ x\le 0\\ 1 & if\ \ x\ge 1\end{cases}$$

and

$$\beta(x)+\beta(1-x)=1,\forall x\in[0,1]$$

The τ_n is defined as $\omega_n:\tau_n=\gamma\omega_n,0<\gamma<1,\forall\, n>0$. Now the above equations gets simplified as,

$$\hat{\phi}_n(\omega)=\begin{cases}1 & if\ \ |\omega|\le\omega_n-\tau_n\\ \cos[\frac{\pi}{2}\beta(\frac{1}{2\gamma\omega_n}(|\omega|-(1-\gamma)\omega_n)] & \\ & if\ \ (1-\gamma)\omega_n)\le|\omega|\le(1+\gamma)\omega_n)\\ 0 & otherwise\end{cases}$$

$$\hat{\psi}_n(\omega)=\begin{cases}1 & if\ \ (1+\gamma)\omega_n\le|\omega|\le(1-\gamma))\omega_{n+1}\\ \cos[\frac{\pi}{2}\beta(\frac{1}{2\gamma\omega_{n+1}}(|\omega|-(1-\gamma)\omega_{n+1}))] & \\ & if\ \ (1-\gamma)\omega_{n+1}\le|\omega|\le(1+\gamma)\omega_{n+1}\\ \sin[\frac{\pi}{2}\beta(\frac{1}{2\gamma\omega_n}(|\omega|-(1-\gamma)\omega_n))] & \\ & if\ \ (1-\gamma)\omega_n\le|\omega|\le(1+\gamma)\omega_n\\ 0 & otherwise\end{cases}$$

Now for a function f, the detail coefficients is obtained by taking the inverse of convolution operation between f and ψ_n. In spectrum domain, the convoluted output is obtained through simple multiplication of the two functions.

$$W_f^{\varepsilon}(n,t)=((\hat{f}(\omega))\overline{\hat{\psi}_n(\omega))^{-1}}\%=\langle f,\psi_n\rangle$$

The approximate coefficients are obtained by taking the inverse of convolution operation between f and ϕ_n

$$W_f^{\varepsilon}(0,t)=((\hat{f}(\omega))\overline{\hat{\phi}_1(\omega))^{-1}}\%=\langle f,\phi_1\rangle$$

Therefore the signal $f(t)$ can be reconstructed as,

$$f(t)=\left((0,\omega)*(\omega)+\sum_{n=1}^{N}(n,\omega)*(\omega)\right)^{-1}$$

The empirical mode function f_k is given as,

$$f_0(t)=W_f^{\varepsilon}(0,t)*\phi_1(t)$$

$$f_k(t)=W_f^{\varepsilon}(k,t)*\phi_k(t)$$

3. Proposed Method

We propose a method to build composite image from a high resolution panchromatic image and a low resolution multispectral image using EWT. Primarily, we define the Empirical Wavelet Transform parameters say, (length of the filter, degree for polynomial interpolation, detection method, and maximum number of bands for detection method) for the source images. EWT decomposes each band say, (band1, band2, ... band M) of the source images into several modes. The decomposition of modes are in the increasing order of frequency from mode1 to mode N. The simple average fusion rule is performed between the corresponding modes of panchromatic image and multispectral image taken one band at a time. Very basic operations like pixel selection, addition, subtraction or averaging are performed by image fusion techniques. Simple Average[13,14] is an easy fusion algorithm in which, mean intensity of corresponding pixels of input images are taken to obtain the resultant fused image. These outputs are subjected to IEWT. The same process is repeated for all bands in multispectral image. Finally, all these bands are concatenated to reconstruct the fused image. The flow diagram of the proposed method is shown in Fig. 1. In the proposed EWT based fusion method, the input image can be considered as 2D signal. By using the 1D-EWT defined in section II, the input images are processed in rows and columns separately. In the proposed method, the number of mode splitting in EWT is given as 2, hence each input image is decomposed into four modes, 2 modes horizontally and 2 modes vertically. Simple average is computed between mode1 of panchromatic image and mode1 of first band of multispectral image. The same is done for mode2, mode3, and mode4 of panchromatic image and first band of multispectral image. These four fused modes are subjected to IEWT. The whole process is iterated for all the bands in multispectral image.

4. Experimental Results and Analysis

The proposed EWT based fusion method is experimented on four datasets. Dataset 1 is a pair of multispectral (2-m resolution) and panchromatic (50cm resolution) image of the location Sydney, Australia captured by the high resolution earth observation satellite WorldView-2. Dataset 2 is Quick- Bird satellite images (resolution is 60cm panchromatic and 2:4m multispectral) of the location Rajasthan, India. Dataset 3 is panchromatic (50cm resolution) and multispectral (2m resolution) image of the location Capetown, South Africa taken by GeoEye-1 earth observation satellite. Dataset 4 is the satellite images (resolution is 30cm panchromatic and 1:2m multispectral) of the location Adelaide, Australia. The experimental results of proposed method are compared with existing techniques (DWT and MSVD) based on well known image quality metrics.

4.1 Metrics Performance Evaluation

Image fusion algorithm may bring out some amounts of noise into the signal, so testing the quality of fused image is of great importance. A reference image which is assumed to be perfect in quality is compared with the fused image to measure the quality of fused image[15]. Image quality is measured based on well known quality metrics which includes Root Mean Squared Error (RMSE), Relative Average Spectral Error (RASE), Normalized Absolute Error (NAE), Laplacian Mean Squared Error (LMSE) and Spatial quality of the fused image [2].

4.1.1 Root Mean Squared Error (RMSE)

RMSE is the square root of the mean of the square of all the errors. For better quality image, the value of root mean square error should be very low.

$$RMSE = \sqrt{\frac{\sum_{y}\sum_{j}(R_j(y) - F_j(y))^2}{r \times c \times b}}$$

Where y is the pixel, j is the band number, r is the number of rows, c is the number of columns and b is the number of bands.

4.1.2 Relative Average Spectral Error (RASE)

RASE describes the moderate performance of a method. The value expressed has a tendency to decrease, as the attribute of fused image increases[2]. The RASE index is expressed as follows

$$RASE = \frac{100}{R}\sqrt{\frac{1}{B}\sum_{i=1}^{B}(RMSE(n))^2}$$

Where R is the mean radiance of the B spectral bands.

4.1.3 Normalized Absolute Error (NAE)

The image is of poor quality when the value of NAE is large[15]. The NAE is defined as,

$$NAE = \frac{\sum_{i=1}^{p}\sum_{j=1}^{q}\left(\left|R_{ij} - F_{ij}\right|\right)}{\sum_{i=i}^{p}\sum_{j=1}^{q}\left(R_{ij}\right)}$$

Where R_{ij} and F_{ij} are the pixel values of reference and fused image.

4.1.4 Laplacian Mean Squared Error (LMSE)

LMSE[15] is computed depend on the Laplacian value of the expected and obtained data. It is defined as,

$$LMSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\nabla^2 R - \nabla^2 F\right)^2}{\sum_{i=i}^{m}\sum_{j=1}^{n}\left(\nabla^2 R\right)^2}$$

Where R and F are reference and output images respectively. Laplacian operator is defined by the following expression,

$$\nabla^2 u = \delta^2 u + \frac{\delta^2 u}{\delta^2 x \delta^2 y}$$

Where u be defined as a function of (x, y). LMSE value is 0, when the fused image and reference image is similar.

4.1.5 Spatial Information

The spatial quality of the fused image is better when the edge data of the fused image has close resemblance with edge data of the input image. To analyze the spatial quality of the fused image, the high frequency data of the output image is compared with the high frequency data of the input image. The high frequency data is extracted using

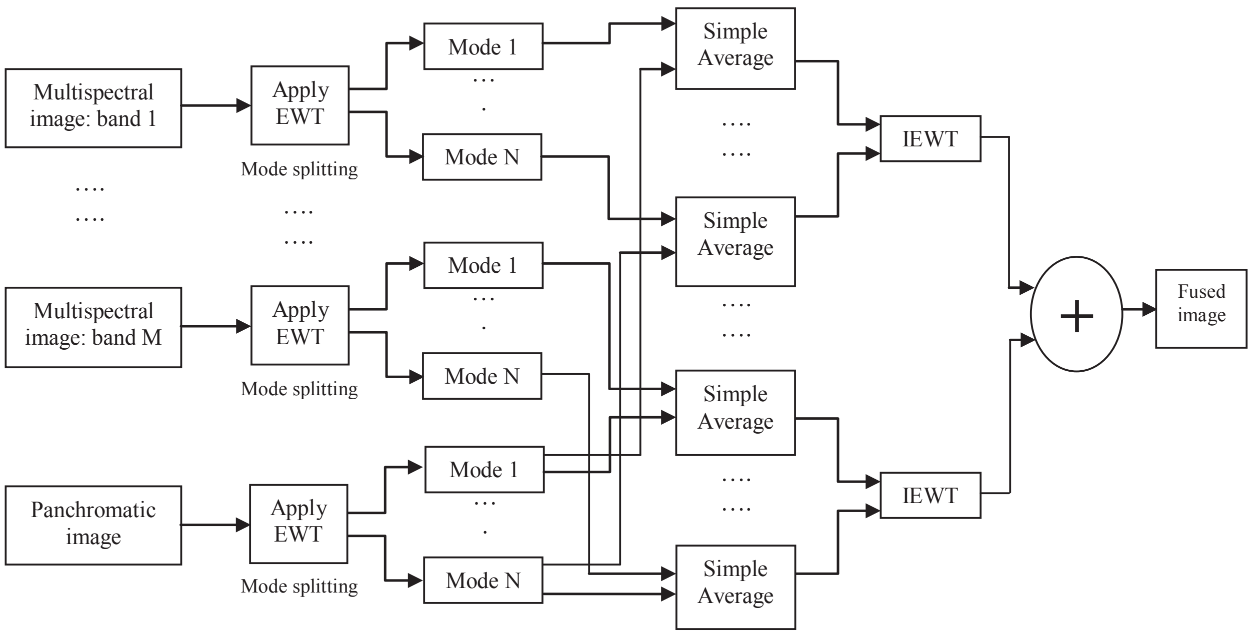


Figure 1. Flow diagram of the proposed method.

the convolution mask[2]. For better quality image, the value of spatial data must be 1.

The above stated metrics are used to conclude which image fusion method performs best spectrally.

5. Results and Discussion

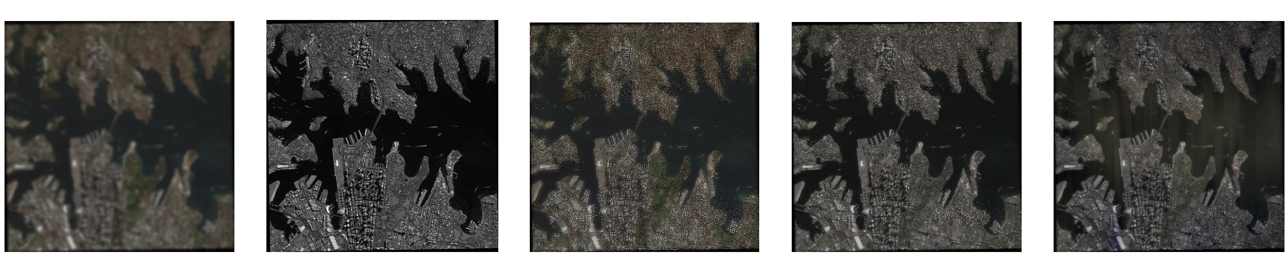
This section gives the comparison of proposed method with existing fusion methods by visual perception and also based on the computation of quality metrics. Lower value for the metric Root Mean Square Error, Relative Average Spectral Error, Normalized Absolute Error, Laplacian Mean Squared Error and higher value for spatial information implies the improved fused image. The output of the EWT based image

Fusion method and other existing methods are shown in Figure 2. to Figure 5.

The quality metrics calculated for the proposed EWT based image fusion method and for other existing

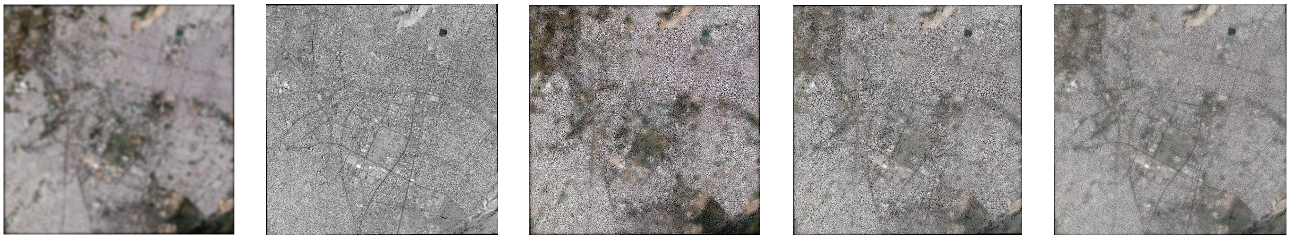
Table 1. Quality metrics calculated for dataset 1

Method	RMSE	RASE	NAE	LMSE	Spatial
Proposed Method (EWT)	19.6369	35.4463	0.2481	0.5868	0.9783
DWT	21.5967	38.9840	0.2572	1.0917	0.9544
MSVD	20.9589	37.8328	0.2856	0.9900	0.6217



(a) (b) (c) (d) (e)

Figure 2. Fused output for dataset 1 (a) Multispectral image, (b) Panchromatic image, (c) DWT based fusion, (d) MSVD based fusion and (e) Output of proposed method (EWT)



(a) (b) (c) (d) (e)

Figure 3. Fused output for dataset 2. (a) Multispectral image, (b):Panchromatic image, (c):DWT based fusion, (d):MSVD based fusion and (e) Output of proposed method(EWT)

(a) (b) (c) (d) (e)

Figure 4 Fused output for dataset 3 (a) Multispectral image, (b) Panchromatic image, (c) MSVD based fusion, (d) DWT based fusion and (e) Output of proposed method (EWT)

(a) (b) (c) (d) (e)

Figure 5. Fused output for dataset 4 (a) Multispectral image, (b) Panchromatic image, (c) DWT based fusion, (d) MSVD based fusion and (e) Output of proposed method (EWT)

Table 2. Quality metrics calculated for dataset 2

Method	RMSE	RASE	NAE	LMSE	Spatial
Proposed Method(EWT)	48.8925	36.6991	0.2950	0.7817	0.9818
DWT	53.4701	40.1350	0.3104	1.2140	0.9828
MSVD	54.0817	40.5941	0.3171	1.1986	0.6217

Table 3. Quality metrics calculated for dataset 3

Method	RMSE	RASE	NAE	LMSE	Spatial
Proposed Method(EWT)	18.6465	28.1730	0.2280	0.6750	0.9820
DWT	19.0601	28.7979	0.2026	0.8842	0.9704
MSVD	20.6897	31.2574	0.2478	0.9776	0.9614

Table 4. Quality metrics calculated for dataset 4

Method	RMSE	RASE	NAE	LMSE	Spatial
Proposed Method(EWT)	26.5761	30.0743	0.2339	0.6684	0.9815
DWT	27.2674	30.8567	0.2285	0.8351	0.9654
MSVD	26.3709	29.8422	0.2264	0.8410	0.6300

methods are presented in Table I to Table IV. The Root Mean Squared Error value for dataset 1 is 19.6369 for proposed EWT based method whereas; the value is high for other existing methods which show that the quality of output of EWT based fusion method is better. The spatial data metric of our proposed method is in the range of 0.97 to 0.98 for all datasets. The RASE value calculated for dataset 2 is 36.6991 for proposed method which is very much less than the value obtained for other existing techniques. The quality of the fused output image will be high when the value for the Laplacian Mean squared Error is minimum. The value of LMSE for the proposed method is very much less than the value obtained for other existing methods.

Visual perception and the quality metric calculated for all datasets used in this experiment shows that the performance of EWT based fusion method is better than the other existing methods. Therefore it can be concluded that the proposed Empirical Wavelet Transform based Fusion of multispectral and panchromatic image is able to preserve the detail features of the original image.

6. Conclusion

In the present work, a new method for fusion of multispectral and panchromatic satellite images has been proposed based on Empirical Wavelet transform. Experiments are done with various satellite images. Visual interpretation and quality metrics (RMSE, RASE, NAE, LMSE, Spatial data) are employed for evaluation of fused image. Experimental analysis proves that the results generated by the proposed method are comparable to results obtained using other methods considered.

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