Comparison between Substitutive and Additive Wavelet Image Fusion using Improved Nonlinear IHS Transform

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Abstract: Several researchers have proposed several methods of image fusion of multispectral (MS) and panchromatic (PAN) that gives satisfactory results. Although, these methods even not touched out of gamut problem, that occurred when pixel value falls out of RGB cube that leads to color distortion. In this paper improved nonlinear IHS transform is used that solves the gamut problem. But due to the large intensity difference between MS and PAN image and image fusion is carried out using Intensity substitution then color distortion occurs, that violates the property of image fusion i.e. image fusion keeps the spectral quality of original image with high spatial resolution. In this paper wavelet based methods are proposed based on additive and substitutive wavelet methods. The wavelet transform is performed with popular methods like in case of additive wavelet fusion using 'a trous' wavelet transform and in case of substitutive wavelet fusion using Mallat's wavelet transform. These methods analyzed both visually and quantitatively.

1. INTRODUCTION

Satellite imagery provides Earth observation images have been offering images with high spatial and spectral resolution. These are obtained by a combining spatial information from PAN image and color information from MS image. These MS and PAN images are acquired by at the same time by sensors lodged at the same space platform. For example IKONOS and Quick Bird satellite imagery. The design constrains of the satellite sensors which produce PAN and MS images distinctly, there is inverse relation between their spectral and spatial resolution. Sensors with high spectral resolution do not shown high spectral resolution and vice versa.

Ideal Image Fusion preserves the spectral quality of the MS image by regaining the spectral quality of PAN image. Each pixel in RGB cube I mapped to IHS color space, due to which each component of RGB pixel such as Intensity, Hue and saturation are manipulated intuitively. In image fusion intensity of pixel is changed by scaling saturation keeping hue constant. The image fusion process is illustrated as fallows [1];



Fig. 1: Illustration of Image Fusion using IHS Transformation using intensity substitution

A. Linear IHS transformation

Linear IHS transformation in the RGB cube is nothing but the direct color shifting [2]. Linear RGB to IHS conversion and its inverse is given as fallows [3];

a. RGB to IHS Conversion. $[i h s]^T = A \times [r g b]^T$

Where,

$$A = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ -\sqrt{2}/6 & -\sqrt{2}/6 & 2\sqrt{2}/6 \\ 1/\sqrt{2} & -1/\sqrt{2} & 0 \end{bmatrix}$$

b. IHS to RGB conversion $[r'g'b']^T = B \times [i'h's']^T$

Where,

$$B = \begin{bmatrix} 1 & -1/\sqrt{2} & 1/\sqrt{2} \\ 1 & -1/\sqrt{2} & -1/\sqrt{2} \\ 1 & \sqrt{2} & 0 \end{bmatrix}$$

By the above transformations, the effect of conducting intensity substitution $i'=i + \delta$ in the IHS space may be shown to be just a direct color shifting in the originalRGB space as follows [2]:

$$[r'g'b']^{T} = B \times [i'h's']^{T} = B \times [i+\delta hs]^{T} = [rg b]^{T} + [\delta hs]^{T}$$

B. Nonlinear IHS transformation

Nonlinear IHS transformation in the RGB cube is nothing but the scaling operation [2]. The graphical model for nonlinear IHS color space is shown in fig. 3(b). The nonlinear IHS transformation also called HSI color transformation and its inverse is defined as fallows [4];

a. RGB to HSI Conversion

$$I = \frac{(R + G + B)}{3}$$

$$a = \frac{(2B - G - R)/2}{\sqrt{(B - G)^2 + (B - R)(G - R)}}$$

$$H = \begin{cases} \cos^{-1}(a) & \text{if } G \ge R\\ 2\pi - \cos^{-1}(a) & \text{if } G < R \end{cases}$$

$$S = 1 - \frac{3\min(R, G, B)}{R + G + B}$$

b. HSI to RGB Conversion

% SECTION RG
$$(0^\circ \le H < 120^\circ)$$

 $B = I(1 - S);$
 $R = I\left[1 + \frac{SCOS(H)}{COS(60^\circ - H)}\right];$
 $G = 3I - (R + B);$
% SECTION GB $(120^\circ \le H \le 240^\circ)$

%SECTION GB (120°
$$\leq H < 240°$$
)
 $R = I(1 - S);$
 $G = I \left[1 + \frac{SCOS(H - 120°)}{COS(180° - H)} \right];$
 $B = 3I - (R + G);$

% SECTION BR(240° $\leq H < 360°$) G = I(1 - S); $B = I\left[1 + \frac{SCOS(H - 240°)}{COS(300° - H)}\right];$

$$B = 3I - (R + B);$$

The linear IHS and nonlinear IHS not touched the out of gamut problem. In this paper improved nonlinear HIS transform which solves the gamut problem by adjusting saturation of a pixel to maximum attainable range. The nonlinear improved RGB to IHS conversion is given as fallows [5];

 $\delta \delta$ The boundary surface BS_{INIMS} two halves is

given as;

•
$$t = \frac{2}{3} - \frac{\left\|h_{mod \ 120} - 60\right\|}{180};$$

 The algorithm for RGB to iNIHS is as fallows;

$$tf t_{\sigma} \leq \frac{2}{2} - \frac{\|h_{mod 120} - 60\|}{150}$$
 then

% Pixel C is in H_{LOWER}

% RGB to IHS transformation

else

% Pixel C is in HUPPER

% CMY to IHS transformation

For the lower half of the improved nonlinear IHS model, use the above explained RGB to IHS transformation equations and IHS to RGB equations. And for the upper half that is above the boundary surface, use CMY to IHS transformation, CMY model is given as [C, M, Y] = [1 - R, 1 - G, 1 - B].

Though the gamut problem is solved, due to the large intensity difference between MS and PAN image leads to color distortion in the fused image. To minimize color distortion, rather than direct intensity substitution in MS image, we only embed spatial details from PAN image to MS image.

2. PROPOSED METHODS

Multi-resolution analysis becomes a suitable tool for the development of new image fusion methods, several researchers have proposed different image fusion procedures using multi-resolution analysis based on Discrete Wavelet Transform (DWT), and proved that those methods provide an improved spatial resolution image, while keeping the spectral properties of the original multispectral

image[6].DWT is based on wavelet theory, allows decomposition of image into different frequency component with the resolution matched to its size. Different resolution of image characterizes different physical features of a scene such as courser resolution details corresponds to larger structures while at a more detailed resolution corresponds to smaller structures. The wavelet transform provides the decomposing image to decreasing degree of resolution representing different levels of detail information of the image between two successive approximation images.

The discrete approach of wavelet transform can be carried out with different algorithms are as fallows [6];

a) Mallat's Algorithm

Mallat's algorithm is an orthogonal, dyadic, nonsymmetric, decimated non-redundant DWT algorithm [6]. Mallat's algorithm is nothing but the pyramid, in which each layer is derived from exactly lower level, is nothing but approximation to the original image. At the Nth layer the approximation image has $R/2^N$ and $C/2^N$. The difference between two consecutive layers represents the detail information is computed using wavelet transform. Three wavelet coefficient images DH_2^{j-1} , DV_2^{j-1} and DD_2^{j-1} represents horizontal vertical and A_2^j and A_2^{j-1} reply. The original image A_2^j is constructed exactly from the A_2^{j-1} and wavelet coefficients DH_2^{j-1} , DV_2^{j-1} and DD_2^{j-1}



Fig. 1 Mallat's Orthogonal Wavelet Transform representation

b) A trous Algorithm

A trous algorithm is a non-orthogonal, dyadic, symmetric, un-decimated redundant DWT algorithm [6]. In this scheme image decomposition scheme is represented as parallelepiped. The base of parallelepiped i.e. original image A_2^{j} is of resolution

 2^{j} , each level in the parallelepiped is approximation to the original image. When climbing up to the parallelepiped each level has courser spatial resolution but having same number of pixels. The A trous algorithm is graphically shown as below;



Fig. 2: A trous non-orthogonal Wavelet Transform representation

3. IMAGE FUSION BASED ON DWT

a) Additive Wavelet Fusion

The steps for additive wavelet fusion are as fallow;

- 1) Apply the iNIHS transform to the RGB composition of the multispectral image. This transformation separates the spatial information of the multispectral image into the Intensity component.
- 2) Generate a new panchromatic image, whose histogram matches the histogram of the Intensity image.
- 3) Apply wavelet decomposition algorithm to the Intensity image and to the 'histogram-matched' panchromatic one. Both second level decompositions are computed using the Daubechies four-coefficient wavelet basis. Extract the wavelet coefficients that pick up the horizontal, vertical and diagonal spatial details present in the panchromatic image and missing in the multispectral image.
- 4) Add this spatial detail information into the Intensity image, by adding the wavelet coefficients of the PAN image to those of multispectral, applying the inverse wavelet transform.

The additive wavelet fusion is graphically shown as below;



- Fig. 3: Additive Wavelet Image Fusion using improved nonlinear IHStransformation
- b) Substitutive Wavelet Fusion

The algorithm for substitutive wavelet fusion is graphically shown as below;



Fig. 4: Additive Wavelet Image Fusion using improved nonlinear IHS transformation

4. EXPERIMENTAL RESULTS AND ANALYSIS

a) Visual Analysis:

The multispectral images are downloaded from Quick Bird. Artificial dataset for image fusion i.e. multispectral (MS) and panchromatic (PAN) images are derived from given satellite multispectral image. The generation of dataset for image fusion is as fallows;

- 1) Let the given satellite image be I.
- 2) Transform the image Iinto gray image G.
- 3) Equalize the histogram of image G, and take the result as PAN image.
- 4) Down-sample I to its original resolution to get generated MS image I'.
 - 5) Darken I' or brighten G so that the intensity values of PAN (G) image are higher than the MS (I').
 - 6) Image fusion is carried out on PAN (G) and MS (I') image.



Fig. 5 a) MS image b) PAN image c) Image fusion using additive wavelet d) Image Fusion using substitutive wavelet

b) Quantitative Analysis:

The quantitative analysis of methods of image fusion is carried out by the measures Spatial Coefficient (SC), Root Mean Square Error (RMSE), Correlation Coefficient (CC).

1. The RMSE between original MS image and fused image is given as[7];

$$RMSE = \sqrt{(\delta_{ms} - \delta_{fused})^2 + (m_{ms} - m_{fused})^2}$$
$$(0 <= RMSE <= 1)$$

Lower the RMSE value, more the correspondence between MS and Fused image.

2. The Correlation Coefficient between MS image and result of image fusion is given as; $r = \frac{\sum_{i} (xi - xm) (yi - ym)}{\sqrt{\sum_{i} (xi - xm)^2} \sqrt{\sum_{i} (xi - xm)^2}}$ (-1<=Correlation Coefficient<=+1)

The value close to +1 means MS and Fused images are more similar, while close to -1 means both images more dissimilar.

3. The spatial quality analysis is done using spatial coefficient. The filter used is Laplacian as illustrated in the following equation[7];

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

The correlation coefficient between high-pass filtered Fused image and high pass filtered PAN image is used to get spatial coefficient whose value is in the range of $0 \le$ Spatial Coefficient ≤ 1 . More the value more spatial similarity between fused and MS image.

The quantitative results of the image fusion using additive wavelet and substitutive wavelet using improved nonlinear IHS image fusion are as fallows;

Method	Datase	Spatial	RMSE	Correlat
	-t	Coeffici		-ion
		ents		Coeffici
				ent
Additive	1	0.687	0.051	0.939
Wavelet	2	0.781	0.088	0.953
	3	0.679	0.023	0.979
Substituti	1	0.736	0.053	0.941
-ve	2	0.832	0.06	0.977
Wavelet	3	0.679	0.019	0.986

Table 1 Quantitative analysis of image fusion	using
additive and substitutive wavelet	

5. CONCLUSION

IHS image fusion had not touched gamut problem, which is solved using improved nonlinear IHS transform. Though the gamut problem was solved, due to the large intensity difference between MS and PAN image fused image shows color distortion. This paper proposes wavelet based methods which embed spatial information from PAN image to MS image rather than direct intensity substitution. Additive image fusion is non-orthogonal and un-decimated that's why it is more popular than Mallat's orthogonal and decimated DWT algorithm. When two algorithms i.e. A trous additive wavelet and Mallat's substitutive wavelet, substitutive wavelet shows better results than additive wavelet. So, substitutive wavelet is good method for image fusion than methods proposed so far. Future work will be based on sharpening MS image without image fusion techniques.

6. **REFERENCES**

 [1] Y. Zhang, "Understanding image fusion," *Photogramm. Eng. Remote Sens.*, vol.70, no. 6, pp. 657–661, 2004.

[2] Chun-Liang Chien and Wen-Hsiang Tsai, "Image Fusion With No Gamut Problem by Improved Nonlinear IHS Transforms for Remote Sensing", IEEE Transactions on Geoscience And Remote Sensing, Vol. 52, No. 1, January 2014.

[3] T. M. Tu, S. C. Su, H. C. Shyu, and P. S. Huang, "A new look at IHS-like image fusion methods," *Inform Fusion*, vol. 2, no. 3, pp. 177-186, 2001.

[4] R. C. Gonzalez, and R. E. Woods, *Digital image processing*, Upper Saddle River, New Jersey, USA: Prentice Hall, 2007.

[5] Chun-Liang Chien and Wen-Hsiang Tsai, "Image Fusion With No Gamut Problem by Improved Nonlinear IHS Transforms for Remote Sensing", IEEE Transactions on Geoscience And Remote Sensing, Vol. 52, No. 1, January 2014.

[6] M. González-Audícana, X. Otazu, O. Fors, and A. Seco, "Comparison between Mallat's and the 'a trous'Discrete wavelet transform based algorithms for the fusion of multispectral and panchromatic images,"*Int. J.Remote Sens.*, vol. 26, no. 3, pp. 595–614, Feb. 2005.

[7] Gang Hong, Yun Zhang, and Bryan Mercer, "A Wavelet and IHS Integration Method to Fuse high Resolution SAR with Moderate Resolution Multispectral Images", Photographic Engineering and Remote Sensing, Vol. 75, No. 10, October 2009, pp. 1213-1223.