A Wavelet Package-Based Data Fusion Method for Multitemporal Remote Sensing Image Processing

Qu Jishuang[1, 2], Wang Chao[1]
[1]Institute of Remote Sensing Application, CAS.
[2]Dept. Automation Control, National University of Defense Technology, China.

ABSTRACT

Data fusion technique is a powerful tool for extracting higher quality information from large amount remote sensing images and eliminating redundancy among these images. There are many image fusion methods so far, such as IHS, PCA, WT, GLP, etc. Among these methods WT and GLP methods can preserve more images' spectral characters than others. Traditional multiresolution analysis image fusion methods always decompose multisource or multitemporal images into low and high frequency parts, then fuse the low frequency part of each image into one low frequency part, however, do not deal with fusion to the high frequency parts which represent images' details, such as edges, corners, ridges, etc. This paper describes a novel wavelet package-based method to fuse multitemporal images, which uses a wavelet package to further decompose multitemporal images at either low or high frequency parts. Then, at the same level, utilizes a threshold and weight algorithm to fuse the corresponding low frequency parts, at the same time applies Lis high-pass filter on fusing the high frequency parts. After that, the fused image will be restored by IDWT, and the fused image will consist of more detailed information and possess better quality. At last, experiment is performed on two multitemporal images to validate this method.

Keyword data fusion, multiresolution analysis, wavelet transformation, wavelet package

1. INTRODUCTION

More and more remote sensing data acquired have resulted in many puzzles to investigators, that is, how to combine large amount data and abstract higher quality information for users, how to eliminate data redundancy, etc. Data Fusion technique, with a data fusion engine to organize, join, and combine multisource and multitemporal data, provides a powerful tool for these data processing problems. It gradually formed with the development of multisensor and multitemporal data processing methods, regarding multisource data as object, and aimed to acquire higher quality data and information, moreover, provided final decision for all kinds of users.[1] So data fusion technique has been utilized widely in the areas of remote sensing image processing, robotic vision, industry procedure monitoring and control, medical image processing, etc.

In general, data fusion is divided into three levels as Pixel-Level fusion, Feature-Level fusion and Decision-Level fusion, and this paper will only address the pixel-level data fusion.

Pixel-level data fusion's input is original multisource or multitemporal images, which have been registered precisely. The objective is to enhance images, segment images, and classify images, then provide better information for identifying images manually or further feature-level fusion. Among the three data fusion levels, pixel-level fusion is the most mature and has had many fusion methods, which are generally classified as Color Transformations, Statistical and Numerical, and Multiresolution Analysis methods.

Further author information:
Qu Jishuang: qujsh@sina.com;
Wang Chao: cwang@public.bta.net.cn.

Data fusion by color transformations takes advantage of the possibility of presenting data in different color channels, including Intensity, Hue, and Saturation (IHS) approach. Harrison and Jupp completed the inference of IHS transformations equation in 1990. This method divides a standard RGB image into spatial (I) and spectral (H, S) information. There are two kinds of transformations, one is to transform three images channels presented in RGB into I, H, S directly, another is to separate the color channels into its average brightness representing the surface roughness (intensity), its dominant wavelength (hue) and its purity (saturation). IHS method has become a standard procedure in image analysis, with ability of enhancing color of highly correlated data, improving spatial resolution, and fusing disparate data.

Statistical and numerical methods, utilizing mathematical or other approaches to combine data of different bands, include PCA (Principal Component Analysis) and PCS (Principal Component Substitution) methods. PCA method utilizes all channels' data as input and combines multisensor's data into one major part; PCS method regards one channel's data as a major part at first, then substitute it by other channels' data if having better fused result.

Color transformations, statistical and numerical methods don't play well in preserving spectral characters of source image, so the fused image features will be altered to great extent. Therefore, these methods have been replaced by multiresolution analysis-based fusion methods for they show much better result at both enhancing resolution and preserving spectral characters.

2. MULTIRESOLUTION ANALYSIS AND WAVELET PACKAGE DECOMPOSESION

Multiresolution analysis-based image fusion method had formed during 90s' of previous century, with the application of wavelet and multiresolution analysis on image processing. Many investigators are devoting to this research of image fusion processing by multiresolution analysis and resulting in many kinds of new methods. Of these pyramid-based and wavelet-based methods are the most typical.[2, 3]

Burt[4] proposed GP (Gaussian Pyramid) and ELP (Enhanced Laplacian Pyramid) decomposition in 1984. However, GP and ELP methods can only decompose and interpolate image with a decimation factor of 2, which results in much restriction. Kim[5] proposed GLP (Generalized LP) method, which extended LP analysis to all scale paradigms. GLP method possesses good bias. With increase of decomposition and span level, the computation increases very quickly, so it is needed to compromise between accuracy and computation in application.

WT (Wavelet-based Transformation) fusion method decomposes image recursively at first, which means decomposing the low frequency part of previous level. Let I_0 be a grayscale image, after decomposed by wavelet, then the first level decomposition will be:

$$I_0 = I_{LL_1} + I_{LH_1} + I_{HL_1} + I_{HH_1} \tag{1}$$

Generally, I_{LL_1} represents the base image named *Approximations*, the other represents high frequency parts named *Details*, and I_{LH_1}, I_{HL_1}, I_{HH_1} represent Vertical, Horizontal, and Diagonal Details.

And then I_{LL_1} will be decomposed at the second level:

$$I_{LL_1} = I_{LL_2} + I_{LH_2} + I_{HL_2} + I_{HH_2} \tag{2}$$

Recursively, the nth level decomposition will be:

$$I_{LL_{n-1}} = I_{LL_n} + I_{LH_n} + I_{HL_n} + I_{HH_n} \qquad n = 1,2,... \tag{3}$$

So the nth decomposition will comprise $3n+1$ sub-image sequences. Then the $3n+1$ sub-image sequences of nth level will be fused, applying different rules on low and high frequency parts. Finally inverse transformation will be taken to restore fused image, which will possesses much better quality. Figure 1(a) shows the 2-level image decomposition by wavelet transformation, in this figure we can find that just low frequency part of $1st$ decomposition is decomposed at the $2scd$ level. However, other high frequency parts aren't decomposed further.

T.Ranchin and L.Wald[6] proposed a wavelet-based fusion method named ARSIS to improve images' resolution, then they validated this method by fusing a SPOT-XS image (spatial resolution 20m) with a KVR-1000 image (spatial resolution 2m), and the result showed the validity of this method.

WP (Wavelet Package-based) method decomposes every part of previous level recursively, either to low frequency or to high frequency, That is, $I_{LH_{n-1}}$, $I_{HL_{n-1}}$, $I_{HH_{n-1}}$ will also be decomposed as equation (3). So there will be 4^n sub-image sequences at the nth decomposition.

Obviously, this detailed decomposition provides possibility to utilize much more flexible fusion rules to acquire fused result with better quality. In Figure 1(b), compared with Figure 1(a), after decomposing to the three high frequency parts of $1st$ decomposition, there are more than seven detailed parts. We regard the low frequency parts of every part's $2scd$ decomposition as the low frequency parts decomposed by wavelet package at the $2scd$ level, marked as $I_{LL_1LL}, I_{LH_1LL}, I_{HL_1LL}, I_{HH_1LL}$ respectively. However, more computation cost will be held in exchange of more detailed decomposition and applying more flexible fusion rules, and with the increase of decomposition level, computation cost will increase very rapidly.

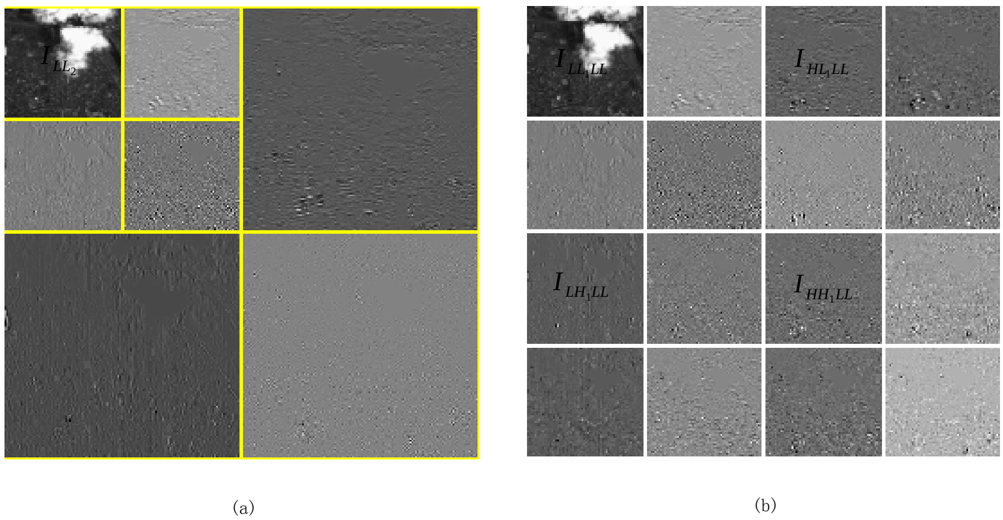


Figure 1. (a) 2-level image decomposition by wavelet transformation; (b) 2-level image decomposition by wavelet package.

3. THRESHOLD AND WEIGHT-BASED IMAGE FUSION ALGORITHM

General WT methods always fuse the low frequency part of images decomposed, sometimes the result by this processing will not be satisfying. So many methods also fusing the high frequency parts have been proposed.

This paper describes a wavelet package-based method to decompose both low frequency part and high frequency parts at each level recursively, and then fuse the different images' corresponding parts at the same level, low frequency parts by threshold and weight, and high frequency parts by high-pass filtering. Figure 2 shows the WP-based fusion procedure. Two images registered precisely are decomposed by a wavelet package, then low frequency parts and high frequency parts are fused by different fusion rules. After that the all fused parts are restored to a fused image by IDWT.

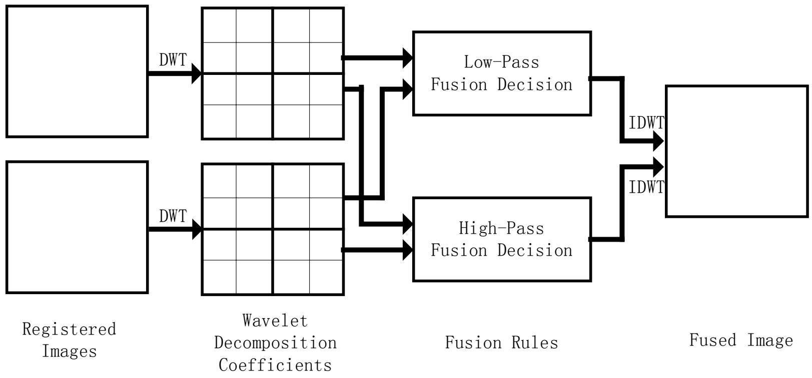


Figure 2. Flow of Wavelet Package-based image fusion method. The registered images are decomposed by wavelet package at first, then the low frequency parts and high frequency parts are fused by different rules. Finally, the fused image is restored by IDWT.

In the following we describes an threshold and weight-based fusion algorithm for low frequency parts:

For two low frequency sub-image sequences $IM1$ and $IM2$, $IM1(i,j)$ and $IM2(i,j)$ are one pair of pixels of them, then we fuse them as following algorithm:

$$
\begin{aligned}
&if\ abs(IM1(i,j)-IM2(i,j))<Threshold1\\
&\quad IM1(i,j)=\omega_1 * IM1(i,j)+\omega_2 * IM2(i,j);\\
&elseif\ abs(IM1(i,j)-IM2(i,j))>=Threshold1 \,\&\, abs(IM1(i,j)-IM2(i,j))<Threshold2\\
&\quad IM1(i,j)=\omega_3 * IM1(i,j)+\omega_4 * IM2(i,j);\\
&if\ abs(IM1(i,j)-IM2(i,j))>=Threshold2\\
&\quad IM1(i,j)=IM2(i,j);\\
&end
\end{aligned}
$$

In above algorithm, $Threshold1$ and $Threshold2$ are threshold of pixel's values, and $\omega_i \ \ i=1,2,3,4.$ are fusion weight among the pair of pixels sequences. In general, ω_i and ω_{i+1} satisfy $\omega_i+\omega_{i+1}=1 \ \ i=1,3$.

For high frequency parts we utilize Lis high-pass filter to fuse the corresponding sub-image sequences.

Finally, all of fused sub-image sequences are restored recursively and acquires fused image which will possesses much better quality than original image.

4. MULTITEMPORAL IMAGES FUSION EXPERIMENTS

We validated above method by fusing two multitemporal images, there are some areas covered by cloud on one of them and another hasn't cloud covered. At first we registered them accurately with bias less than half pixel. After decomposing these two images, we applied above algorithm and Lis high-pass filter on fusing the low and high frequency parts. Finally the fused image was restored by inverse wavelet transformation.

Figure 3 exhibits the fused result by above method, and the max decomposition level is 2. Figure 3(a) and 3(b) are the original images, and there is cloud at some areas in 3(a) but not in 3(b). Figure 3(c) exhibits the fused result by WT just fusing the low frequency part. Figure 3(d) shows the fused result by general WT method, by which the low frequency part was merged by threshold and weight-based algorithm and the high frequency parts were fused by Lis high-pass filter fusion rules. Figure 3(e) gives the fused result by WP method. At first, we fused the four relative low frequency parts, that is, $I_{LL_1LL}, I_{LH_1LL}, I_{HL_1LL}, I_{HH_1LL}$, by threshold and weight algorithm, and then fused the high frequency parts by Lis high-pass filter. Finally, we restored the fused image by IDWT. The fused result Figure 3(c), 3(d), and 3(e) show that the cloud is removed primarily, however, there is any blur at the cloudy area of original image in 3(c), 3(d) and 3(e)'s quality is much better than 3(c)'s. And 3(e)'s quality is a little better than 3(d)'s, however, 3(d)'s spectral characters preserved are a little better than 3(e)'s.

5. CONCLUSION

In this paper we've analyzed image fusion technique, especially to multiresolution analysis-based methods such as pyramid-based, wavelet-based, and wavelet package-based fusion methods. Generally, WT methods just fuse the low frequency part decomposed. We describes two better fusion methods, one is WT method not only fusing the low frequency part but fusing the high frequency parts by Lis high-pass filter, another is WP method which decomposes both low frequency parts and high frequency parts recursively at each level, and then fuses the low frequency parts by a threshold and weight algorithm, at the same time fuses the high frequency parts by Lis high-pass filter. The fused image will be restored by IDWT. Finally experiments and results are held to validate the methods that the fused image possesses better quality.

ACKNOWLEDGEMENTS

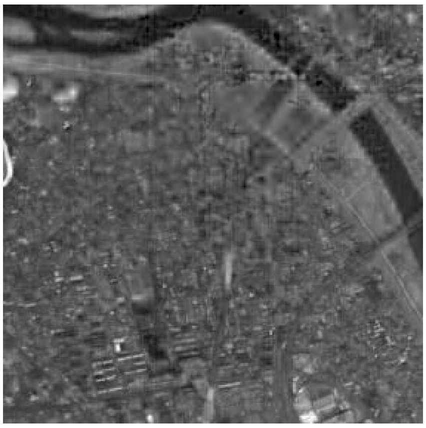
Radar Group of Institute of Remote Sensing Application, CAS supported this research, here I'll express my thanks for Dr. Liu Zhi, Gao Xing, Zhang Hong, and associated professor Guo Ziqi's help.

REFERENCE

1. C. Pohl. Tools and methods used in data fusion. *Future Trends in Remote Sensing. Gudmansen(ed)* © 1998 Balkema. Rotterdam, pp. 391-399 ISBN, 90 5410 933 5.
2. L. Alparone, V. Cappellini, L. Mortelli. A pyramid-based approach to multisensor image data fusion with preservation of spectral signatures. *Future Trends in Remote Sensing. Gudmansen(ed)* © 1998 Balkema. Rotterdam, pp. 419-426 ISBN, 90 5410 933 5.
3. Jorge Núňez, Xavier Otazu, Octavi Fors, Albert Prades, Vicenc Palà, Román Arbiol. Multiresolution-Based Image Fusion with Additive Wavelet Decomposition. *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 3, pp. 1204-1211. May 1999.
4. Burt, P. J. 1984. The Pyramid as a structure for efficient computation. In A. Rosenfeld (ED), *Multiresolution Image Processing and Analysis*, Berlin: Springer-Verlag.
5. M. G. Kim, I. Dinstein, L. Shaw. 1993. A Prototype Filter Design Approach to Pyramid Generation. *IEEE Trans. Pattern Anal Machine Intell* , vol. 15, *No. 12,* pp. 1233- 1240.
6. T. Ranchin, L. Wald. Sensor fusion to improve the spatial resolution of images: The ARSIS methods. *Future Trends in Remote sensing, gudmansen(ed.)* © 1998 Balkema, Rotterdam, pp. 445-451, ISBN 90 5410 933 5.

(a)

(b)



(c)

(d)

(e)

Figure 3. (a) A city remote sensing image with some areas coverd by cloud; (b) A city remote sensing image without cloud; (c) Fused image by WT only fused the low frequency part, the cloud had been removed primarily, but there is any blur in the cloudy area; (d) Fused image by WT fusing both the low frequency part and high frequency parts, and the result is much clearer than (c); (e) Fused image by WP, the definition is a little better than (d)'s, however, the spectral characters preserved are a little worse.