International Journal of Information Technology, Vol. 11, No. 7, 2005

Multisource Image Fusion Based on Wavelet Transform

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Abstract

This paper clarifies the concepts and relationship between image fusion rules and operators based on wavelet transform. According to wavelet decomposition characteristic, a new strategy of calculating spatial frequency is put forward. Fusion experiments are performed on QuickBird panchromatic (PAN)and multispectral (MS) images based on orthogonal and biorthogonal wavelet, in which a method of comparing activity level of spatial frequency is introduced for the detail coefficient fusion. Finally, the influence of the wavelet decomposition level and support width on the results of fusion is discussed in detail.

Keywords: Image fusion, wavelet transform, multisource image, spatial frequency.

1 Introduction

With the availability of multisensor data in many fields, such as remote sensing, medical imaging and machine vision, multisensor data fusion has emerged as a new and promising research area. Modern earth resource satellites have the capability of collecting spatially co-registered panchromatic(PAN) and multispectral(MS) images. Due to high spatial resolution and low spectral resolution of PAN image, and low spatial resolution and high spectral resolution of MS image, image fusion is to combine these two kinds of images to form new images for improving the performances of the fused images in information content, resolution, and reliability of registration and interpretation.

At first, the previous methods of computing activity level and fusion operator are introduced, and then a new method of computing activity level is proposed in this paper. Multiple criteria and statistical indicators regarding different aspects of image quality are presented for objective and quantitative evaluation of the fused images for understanding the performance of image fusion algorithms.

The paper is organized as following: Section 2 overviews the wavelet transform in image fusion; the image fusion rules and operators are discussed in Section 3; Section 4 describes the experiments on QuickBird PAN and 3-band natural color MS images fusion. Conclusions are drawn in Section 5.

2 Wavelet Transform in Image Fusion

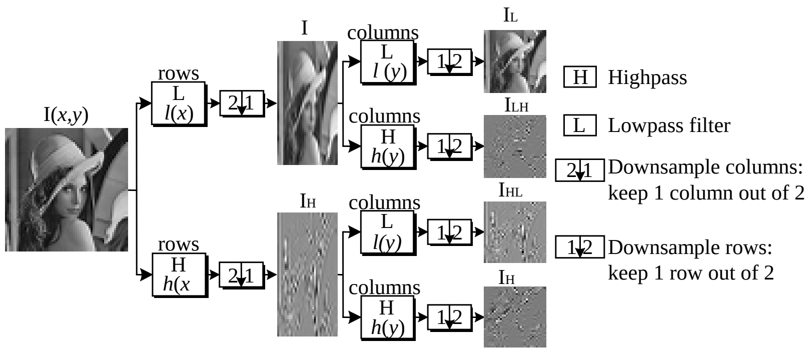

Fig. 1. DWT image decomposition

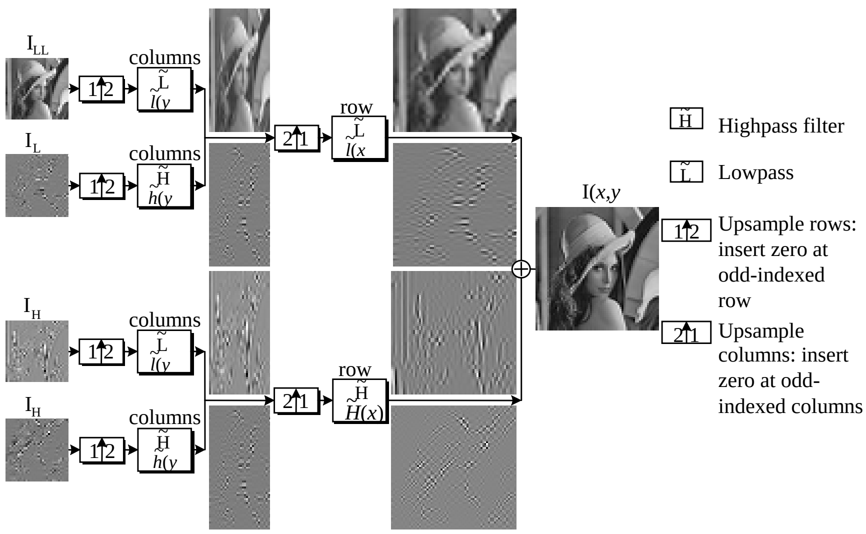

Fig. 2. DWT image reconstruction

In 1984, the concept of wavelet was introduced firstly by French physicist Morlet and theory physicist Grossman. In 1989, Mallat defined the concept of multiresolution analysis(MRA), and put all the methods of wavelet construction into the framework of functional analysis. He also described the fast wavelet transform algorithm and general method of constructing wavelet orthonormal basis. On the basis, wavelet transform can be really applied to image decomposition and reconstruction[1], [2], [3].

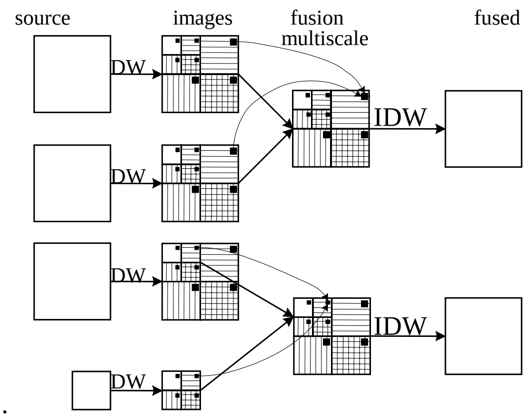

Fig. 3. Generic fusion schemes

Fig.1 depicts one stage in a wavelet multiresolution pyramid decomposition of the input image. Fig.2 shows one stage in wavelet reconstruction. Fig.3 illustrates block diagrams of generic fusion schemes where the input images have identical and different resolutions based on wavelet transform.

3 Fusion Rule and Fusion Operator

In most cases, fusion rule is not distinguished from fusion operator in image fusion field, and the two concepts both reflect to method of image fusion in general. Distinguishing the two concepts is useful to comprehend the image fusion.

Fusion rule is defined as a strategy in the process of image fusion, while fusion operator is fusion method which is adopted in the above fusion rule.

Fusion rule is verified by computing activity level. Activity level is defined as:

$$A_I(p) = f(U(p)) \quad \textbf{(1)}$$

where p is the position of image decomposed coefficient; $U(p)$ is a neighborhood which is centered at point p . f is a function of computing activity level.

There are three methods for computing the activity level of an multiscale decomposition(MSD) coefficient: coefficient-based, window-based and region-based measures[3], [4]. The window-based activity measures employ a small window centered at the coefficient position, which can be computed by several methods here, such as the weighted average, the rank filter and space frequency etc.

Generally, an image has its MSD representation denoted as D_I .Let $p=(m,n,j,l)$ indicate the index corresponding to a particular MSD coefficient, m and n indicate the spatial position in a given frequency band, j is the decomposition level and l is the frequency band of the MSD representation.

3.1 Fusion Rule (Activity Level Measurement)

3.1.1 Weighted Average Method

$$A_I(p)=\sum_{s\in S,t\in T} w(s,t)\left|D_I(m+s,n+t,j,l)\right|^a \tag{2}$$

where $w(s,t)$ is normalized weight, S and T are sets of the current window. If $a=2$, then $A_I(p)$ is called local energy centered at point p by some authors[5], [6].

3.1.2 Rank Filter Method

$$A_I(p)=Rank(i)(Q) \tag{3}$$

The above expression is to pick the i^{th} largest value in the set Q, $Q=\{\left|D_I(m+s,n+t,j,l)\right|, s\in S, t\in T\}$. Usually i is set 1.

3.1.3 Spatial Frequency Method

Spatial frequency proposed by Eskicioglu *etc.* is calculated by horizontal and vertical spatial frequency [7]. It reflects the whole activity level of an image, which means the larger of spatial frequency, the higher of image resolution.

We expand the concept by adding diagonal frequency into the calculation of spatial frequency. Then spatial frequency includes horizontal, vertical and diagonal frequency. It is similar to wavelet decomposition that can obtain horizontal, vertical and diagonal detail band. For an $M\times N$ image block, the spatial frequency is defined as:

$$A_I(p)=\sqrt{HF^2+VF^2+DF^2} \tag{4}$$

where HF, VF, DF is horizontal, vertical, diagonal frequency respectively: $HF=\sqrt{\sum_{m=1}^{M}\sum_{n=2}^{N}(f_{m,n}-f_{m,n-1})^2 \Big/ M(N-1)}$, $VF=\sqrt{\sum_{m=2}^{M}\sum_{n=1}^{N}(f_{m,n}-f_{m-1,n})^2 \Big/ (M-1)N}$,

$$DF=\sqrt{\sum_{m=2}^{M}\sum_{n=2}^{N}(f_{m,n}-f_{m-1,n-1})^2 \Big/ (M-1)(N-1)}+\sqrt{\sum_{m=2}^{M}\sum_{n=2}^{N}(f_{m-1,n}-f_{m,n-1})^2 \Big/ (M-1)(N-1)}$$

3.1.4 Standard Deviation Method

Standard deviation denotes the deviation degree of the estimation and the average of the random variable, the activity level is estimated by standard deviation as follows:

$$A_I(p) = \sqrt{\sum_{s\in S, t\in T} (D_I(m+s, n+t, j, l) - \bar{D}_I(m+s, n+t, j, l))^2 \Big/ S \times T} \quad \textbf{(5)}$$

3.2 Fusion Operator (Fusion Coefficient Method)

3.2.1 Activity Level Comparison

As for the detail of wavelet decomposition, the coefficients are fluctuating around zero, the larger transform values correspond to sharper brightness changes(such as edges and region boundaries). That is reflected by the method of activity level comparison.

$$D_F(p) = \begin{cases} D_A(p) & if \quad A_A(p) > A_B(p) + T \\ D_B(p) & if \quad A_A(p) < A_B(p) - T \\ [D_A(p) + D_B(p)]/2 & other \end{cases} \quad \textbf{(6)}$$

3.2.2 Weighted Average

Match measure is defined as:

$$M_{AB}(p) = \frac{2\sum_{s\in S, t\in T} w(s,t) D_A(m+s, n+t, j, l) D_B(m+s, n+t, j, l)}{A_A(p) + A_B(p)} \quad \textbf{(7)}$$

Let T denote threshold ($0.5 \sim 1$ in general), the weight is estimated as follows:

$$\begin{cases} w_{\min} = 0\,,\ w_{\max} = 1 & M_{AB}(p) < T \\ w_{\min} = \frac{1}{2} - \frac{1}{2}\left(\frac{1 - M_{AB}}{1 - T}\right),\ w_{\max} = 1 - w_{\min} & other \end{cases} \quad \textbf{(8)}$$

Weighted average merging method is formulated as follows:

$$\begin{cases} D_F(p) = w_{\max} D_A(p) + w_{\min} D_B(p) & A_A(p) \ge A_B(p) \\ D_F(p) = w_{\min} D_A(p) + w_{\max} D_B(p) & A_A(p) < A_B(p) \end{cases} \quad \textbf{(9)}$$

3.2.3 Background Elimination

$$D_F(p) = D_A(p) - \mu_A + D_B(p) - \mu_B + (\mu_A + \mu_B)/2 \quad \textbf{(10)}$$

where μ_A, μ_B are the mean values decomposition coefficients of the image A and B in a given windows respectively. This method ensures that all the background information presented in the input images gets transferred into the fused image.

4 Experiment and Analysis

To prove the efficiencies of the different fusion rules and fusion operators, we performed many experiments under MATLAB® 6.5 on Intel® Pentium IV PC.

4.1 Image Fusion Experiment

In the following experiments, we choose spatial frequency defined in this paper as fusion rule and activity level comparison method as fusion operator.

As spatial frequency reflects image resolution, the resolution of the fusion image can be improved by comparing spatial frequency. Because activity level comparison of wavelet decomposition coefficient can get the image part which has sharper brightness changes (such as edges and region boundaries), it can express the detailed part of image to get much satisfied fusion results.

We adopt weighted average method to merging approximate image. To make the range of the coefficients consistent with the range of the PAN approximation coefficients under the same resolution, linear transform of the MS approximate image coefficient is computed before the merging.

At the end we take the consistency examination on the fused MSD coefficients.

The two categories of typical wavelets are compared through the fusion experiments: one is the wavelets with the characteristics of orthogonal, compact support and definite vanishing moment such as dbN, symN and coifN, the other is the spline wavelets with the characteristics of biorthogonal, compact support and definite vanishing moment such as bior Nr.Nd.

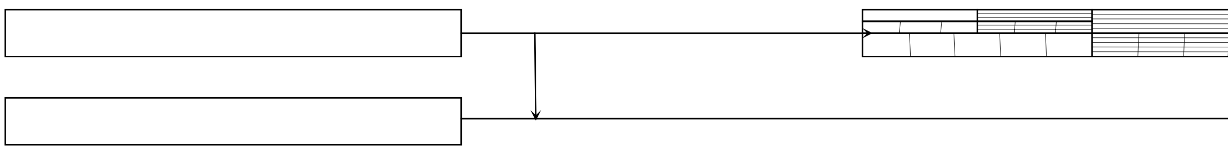

Fig. 4. Schematic diagram for the basic image fusion

Fig.4 illustrates the schematic diagram for the basic image fusion. Fig.5 shows the segmented sub-scenes with 512×512 and 128×128 pixels of the co-registered QuickBird PAN and natural color MS images with ground spacings of 0.61 and 2.44

meter, respectively. In Fig.5, (a), (b), (c) are 3-band of MS images, (d) is color image obtained by (a), (b) and (c), and (e) is high-resolution PAN image(© DigitalGlobe). The MS images displaying rate is 50%, and PAN image is 25%.

Fig. 5. Original PAN and MS images

4.2 Performance Evaluation

There are many methods[8], [9] to estimate the fusion performance of MS and PAN image. Most of them consider the enhancement of spatial detail information and hold of spectrum information. In general, two kinds of statistical indicators should be taken into account: one is the statistical indicators which reflect spatial detail information, such as correlation coefficient of the fused image and the PAN image, resolution of fused image, the other is the indicators that express the spectrum information, such as root mean square error(RMSE), signal noise ratio(SNR).

Let $p(i, j)$ represent original PAN image, $f(i, j, k)$ denote the original MS image of band k resampling to the same size as the PAN image, $g(i, j, k)$ denotes fused image, M and N denotes the size of image.

Image resolution is estimated by ladder method, the formula is:

$$D = \sum \sqrt{\left(\Delta I_x{}^2 + \Delta I_y{}^2\right)/2} \Big/ MN \tag{11}$$

where ΔI_x and ΔI_y are differences in the horizontal and vertical direction respectively.

RMSE:

$$RMSE(k) = \sqrt{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(g(i, j, k) - f(i, j, k))^2 \Big/ MN} \tag{12}$$

SNR:

$$SNR(k) = \sqrt{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} g(i, j, k)^2 \Big/ \sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(g(i, j, k) - f(i, j, k))^2} \tag{13}$$

The correlative coefficient reflects the correlation of two images:

$$CORR(k) = \frac{\sum_{i,j}\left[\left(g(i,j,k)-\overline{g}\right)\left(p(i,j)-\overline{p}\right)\right]}{\sqrt{\sum_{i,j}\left(g(i,j,k)-\overline{g}\right)^2 \sum_{i,j}\left(p(i,j)-\overline{p}\right)^2}} \qquad (\mathbf{14})$$

Fig.6 shows correlation coefficient and RMSE as the statistic indicators between the original image and fused image.

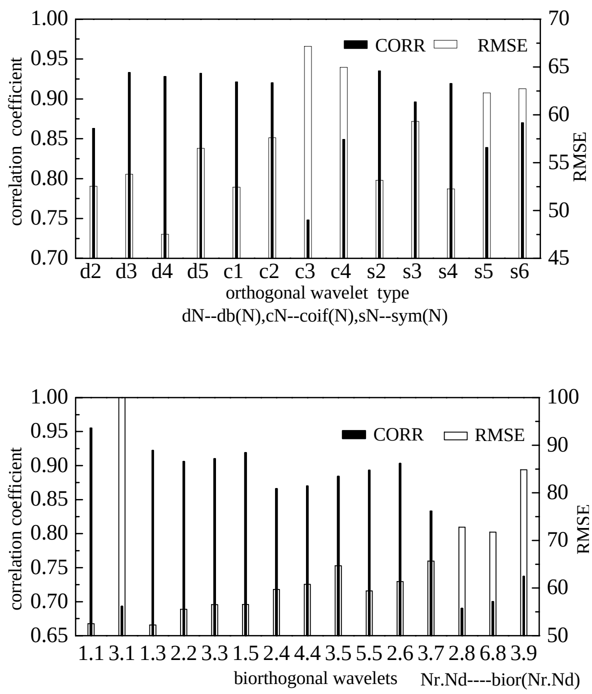

Fig. 6. Statistical indicators between original and fused images

4.3 Experiment Analysis

The experiments show that the level of wavelet decomposition greatly influences fusion performance. In general, wavelet decomposition level should be morn than 3. For these experiments, 128×128 pixels of the MS image decomposition level is 3, and 512×512 pixels of the PAN image decomposition level is 5.

Fig.7 shows parts of fused images got from the experiment results.

Table 1 and Table 2 give statistical indicators of fused images corresponding to Fig.7.

From Fig.6, Fig.7, Table1 and Table2 we can reach conclusion that as for orthogonal wavelet the best results are obtained with db4, followed by coif1, sym4 and sym2, their filter size is 8, 6, 8, 4 respectively, as for biorthogonal wavelet the best results are obtained with bior1.1, followed by bior1.3, bior2.2, bior3.3, bior1.5, their filter size is 2, 6, 6, 8, 10. But notable block efficiency appears in most of the fused images based on biorthogonal wavelet.


db4 fused image


coif1 fused image


sym4 fused image


sym2 fused image


bior2.2 fused image


bior1.3 fused image

Fig. 7. Fused images(displaying rates are 25%)

Table 1. Statistical indicators of Correlation coefficient and Resolution

Filter size	Wavelet type	Correlation coefficient			Resolution		
8	db4	0.929	0.935	0.921	16.606	16.628	16.510
6	coif1	0.923	0.927	0.913	16.587	16.607	16.501
4	sym2	0.936	0.941	0.928	16.448	16.543	16.430
8	sym4	0.920	0.925	0.913	16.485	16.576	16.456
2	bior1.1	0.958	0.961	0.946	16.786	16.849	16.751
4	bior3.1	0.680	0.699	0.699	12.902	12.911	12.854
6	bior1.3	0.922	0.928	0.915	16.716	16.743	16.703
6	bior2.2	0.904	0.912	0.901	15.184	15.367	15.450
8	Bior3.3	0.913	0.918	0.899	15.489	15.752	15.777
10	Bior1.5	0.917	0.927	0.914	15.315	15.781	16.057

Table 2. Statistical indicators of RMSE and SNR

Filter size	Wavelet type	RMSE			SNR		
8	db4	47.967	47.499	47.126	3.345	3.221	3.145
6	coif1	52.841	52.347	52.168	3.038	2.951	2.844
4	sym2	52.651	53.291	53.538	3.006	2.806	2.705
8	sym4	52.731	52.113	51.919	3.080	2.959	2.852
2	bior1.1	52.214	53.059	52.318	2.948	2.759	2.742
4	bior3.1	110.033	109.299	108.653	0.665	0.656	0.645
6	bior1.3	53.115	52.105	51.452	3.106	3.053	2.968
6	bior2.2	58.444	55.650	52.545	3.128	3.167	3.219
8	Bior3.3	58.544	55.950	55.001	3.012	2.963	2.878
10	Bior1.5	59.637	56.145	53.886	3.019	3.021	3.011

5 Conclusions

This paper clarifies the concepts and relationship between the fusion rules and fusion operators in image fusion filed, and proposes a new spatial frequency computing method corresponding to wavelet decomposition characteristic. We carry out fusion experiments on QuickBird MS and PAN images with orthogonal and biorthogonal wavelets using activity level comparing method based on spatial frequency.

We adopt weighted average method to merging approximate image. To make the range of the coefficients consistent with the range of the PAN approximation coefficients under the same resolution, linear transform of the MS approximate image coefficient is computed before the merging. The experimental results show that this method can further better the efficiency of the fusion.

By analyzing the subjective visual effect and objective statistic indicators evaluation, we know that suitable wavelet decomposition levels are of the great most importance to the fusing result. In order to obtain best results, generally, the levels of wavelet decomposition should be more than 3, while the filter size of wavelet transform should be 6 or 8. But notable block efficiency appears in most of the fused images based on biorthogonal wavelet.

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