A new remote sensing image fusion method combining principal component analysis and curvelet transform

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Abstract. In the framework of multi-scale decomposition, a new multi-source image fusion algorithm based on principal component analysis (PCA) and curvelet transform is proposed for pixel-level image fusion. Firstly the low-resolution multi-spectral image is transformed by PCA and principal components are obtained. Secondly the high-resolution image and the first three principal components of the multi-spectral image are respectively merged with curvelet transform and finally the fused image is obtained by inverse PCA transform. This method gives the results of fusion and is compared with the traditional method of PCA, which proves the effectiveness of the method.

1. Introduction

The image fusion refers to acts according to some algorithm and carries on synthesis processing to the image which obtains from the different sensors [1]. Then we can obtain a new image to satisfy some kind of request. The fusion image should be clearer than the original image to distinguish and may use in the image sharpening, image division, target identification and so on. The fusion methods of multi-source image are IHS transform, PCA transform, HPF fusion algorithm, the wavelet transform and so on [1]. The above method has certain limitations. IHS transform fusion easily to have the spectrum degenerate. PCA transform fusion will lose its original physical property. PHF transform fusion filter out majority texture information of high resolution wave band image. And the wavelet transform can only reflect the signal zero dimension singularity characteristic, namely can only reflect strange "point" position and characteristic, but expresses high dimension characteristic with difficulty. In view of the above methods’ weakness, this article proposed one kind fusion algorithm of multi-source image based on PCA and curvelet transform, and has given qualitative appraisal and quantitative evaluation of the image fusion result. The experiments proved that this algorithm can obtain a good fusion effect.

2. The curvelet transform

2.1 The first generation curvelet transform
The curvelet transform is proposed by Candes and Donoho in 1999, its essence is derived from the ridge-wave theory \cite{2}. In the foundation of single ridge-wave or local ridge-wave transform, we can construct Curvelet to express the objects which have curved singular boundary. Curvelet combines the advantages of ridge-wave which is suitable for expressing the lines’ character and wavelet which is suitable for expressing the points’ character and take full advantage of multi-scale analysis, it is suitable for a large class of image processing problems and has got quite good results in practical application. 

Instead of a tilted grid, we assume a regular rectangular grid and define ‘Cartesian’ curvelet in essentially the same way as before,

$$
c(j,l,k) = \int f(\omega)\hat{U}_j(S_{\omega}^{-1}b)e^{i\omega\cdot b}d\omega
$$

Discrete curvelet transform formula

$$
c(j,l,k) = \int f(\omega)\hat{U}_j(S_{\omega}^{-1}b)e^{i\omega\cdot b}d\omega
$$

(2)

Notice that the $S_{\omega}^b$ has been replaced by $b=(k,2^{-l},k,2^{-l})$, taking on values on a rectangular grid. As before, this formula for $b$ is understood when $\theta \in \left[-\frac{\pi}{4}, \frac{\pi}{4}\right]$ or $\theta \in \left[\frac{3\pi}{4}, \frac{5\pi}{4}\right]$.

### 2.2 The second generation curvelet transform

The first generation of curvelet transformation’s digit realizes quite complex. It needs a series of steps: sub-band decomposition; smooth segmentation; Ridge-wave analysis. Moreover the curvelet pyramid’s decomposition has also brought huge data redundancy quantity, therefore E.J.Candes and so on also proposed the fast curvelet transform algorithm which realize simpler and is advantageous for understanding, namely the second generation of curvelet transform \cite{3}. The second generation of curvelet already completely was structurally different with first generation of curvelet. The first generation of curvelet structure thought is approximate the curve to each piecemeal in the straight line through enough small piecemeal, then use partial ridgelet to analyze its characteristic \cite{4}. But the second generation of curvelet theory has not related to ridgelet and realizes the process also not to need with ridgelet. The same spots between them only lie in the tight support, the frame and so on abstract mathematics significance.

### 3. Image fusion method based on PCA and curvelet transform

#### 3.1 The principal component analysis

PCA transform is also called principle components analysis. It is in the statistical nature foundation multi-dimensional orthogonal linear transform. PCA transform widely applies in image compression, stochastic noise signal elimination as well as image orientation and so on \cite{5}. First carries on PCA transform to the low resolution multi-spectrum image and obtains its component variable \cite{6}. Then carries on linearity to the high spectrum image to stretch, enables it to have the same average value and the variance with the first principal component of low resolution multi-spectrum image. Finally, replaces the first principal component after the stretch image, through PCA inverse transform to RGB space, namely obtains the final fusion result image again \cite{7,8}.

#### 3.2 The new fusion method combining PCA and curvelet transform

The goal of curvelet transform is that divide the primitive remote sensing image to a series of frequency channel, after then uses its decomposition structure, to the different decomposition level, different direction frequency band carries on separately fusion processing. Then make an effective fusion of different image details.

This article used the superiority of curvelet transform and made the improvement in PCA transformation’s foundation. It proposed one kind of new image fusion algorithm. The concrete step is as follows:
1) First carries on PCA transform to the low resolution multi-spectrum image and obtains its component variable. pca1_MUL, pca2_MUL, pca3_MUL…

2) Then carries on linearity to the high spectrum image to stretch, enables it to have the same average value and the variance with the first three principal components of low resolution multi-spectrum image.HR1, HR2, HR3.

3) Carries on curvelet transform after step (1) multi-spectrum image’s first three components pca1_MUL, pca2_MUL, pca3_MUL and the matched high resolution image HR1, HR2, HR3, obtains the coefficient C1_MUL, C_MUL, C3_MUL, C1_HR, C2_HR, C3_HR.

4) Make the adjustment using certain criterion to the transformation ratio. Averages to the most inner layer coefficient, obtains richer low frequency information; other each level takes the absolute value biggest coefficient, obtains the more spatial detail information. The adjustment coefficients are CC1, CC2, and CC3.

5) Using the new curvelet transform ratio which step (4) obtain carries on the inverse transformation, obtain result component of high resolution and good maintained primitive image spectral signatures pca1_HR, pca2_HR, pca3_HR.

6) Finally through PCA inverse transform to RGB space, namely obtains the final fusion result image.

4. Experimental results

4.1 The evaluating indicator

1) Average

The average value is the mean value of all pixels in the image.

\[ \bar{f} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} f(i, j) \]  

where \( M \times N \) represents the size of image \( f \), \( f(i, j) \) represents the grey value of point \((i, j)\) in image \( f \).

2) Standard deviation

Standard deviation is an important target of weighing image information rich degree.

\[ \text{std}(f) = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (f(i, j) - \bar{f})^2} \]  

3) Information entropy

The image information entropy is its information content measure. The entropy is bigger, the image contains the information is richer, the picture quality is better.

According to Shannon information theory, the entropy of an image of 8bit is:

\[ H(f) = -\sum_{i=0}^{255} P_i \log_2 P_i \]  

In the formula, \( P_i \) represents the probability of \( i \) pixel value.

Moreover, Chavez (American1984) proposed the best index expresses the entropy of multi-wave image.

\[ OIF = \frac{\sum_{i=1}^{n} \text{std}_i}{\sum_{i=1}^{n} \sum_{j=1}^{n} R_{i,j}} \]  

where \( \text{std}_i \) represents standard deviation of \( i \) band; \( R_{i,j} \) represents correlation coefficient between \( i \) and \( j \) band.

4) Clarity
The image clarity may use the average gradient to weigh.

\[ T = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \sqrt{(I_x^2 + I_y^2) / 2} \]  \hspace{1cm} (7)

\[ I_x = f(i+1, j) - f(i, j) \] \hspace{1cm} (8)
\[ I_y = f(i, j+1) - f(i, j) \]

5) Deviation index (spectrum distortion degree)

Costantn and so on used deviation index to reflect fusion image and primitive image in spectrum information match degree.

\[ WARP = \frac{1}{M * N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left| \frac{g(i, j) - f(i, j)}{f(i, j)} \right| \]  \hspace{1cm} (9)

where \( g(i, j) \) is grey value of fusion image \( g(i,j) \), \( f(i, j) \) is grey value of primitive multi-spectrum image \( f(i,j) \).

4.2 Experimental results

In this experiment, take Erdas example image dmtm.img and spots.img as data sources. We use two-dimensional wavelet, PCA transform and the new fusion method based on Curvelet and PCA transform respectively to fusion image. Fusion results see Fig.1 and evaluating indicator value see Table 1.
Figure 1. Fusion result on SPOT panchromatic and multi-spectrum images

Table 1. Quality evaluation of fusion results

| Method        | Band | Average Distortion degree | Clarity | Entropy | OIF     | Std     |
|---------------|------|---------------------------|---------|---------|---------|---------|
| Curvelet and PCA | NIR  | 127.5107 38.1775   | 16.3938 | 5.9783  | 29.1955 | 74.8076 |
|               | R    | 127.5567 41.0130   | 47.4937 | 5.9782  | 74.8186 |         |
|               | G    | 127.8739 45.9995   | 54.9287 | 5.8610  | 74.2109 |         |
| PCA           | NIR  | 127.6246 49.8291   | 47.1836 | 5.9383  | 27.2796 | 74.8410 |
|               | R    | 127.5567 46.6690   | 48.6897 | 5.9402  | 74.7033 | 74.8958 |
|               | G    | 127.6751 45.8605   | 49.5254 | 5.9453  | 74.9178 | 75.0125 |
| Wavelet       | NIR  | 127.5197 38.7255   | 30.5551 | 5.9785  | 25.8361 | 74.9085 |
|               | R    | 127.6079 34.1523   | 31.7539 | 5.9453  |         | 75.0125 |
|               | G    | 127.6389 33.6189   | 31.3555 | 5.9453  |         | 74.9178 |

From Table 1, we could see that these three methods’ various wave bands’ average value and the standard deviation difference are not big. In the information entropy aspect, the improvement algorithm’s OIF index is higher than other method fusion images. This explained after improvement algorithm fusion image contains information content is bigger, information opposition is strong and redundancy is small. The improved algorithm’s clarity value is lower than PCA transform and higher than wavelet transform. The clarity had reflected the gradation rate of change. The clarity is bigger, the image is clearer. Therefore, the improvement algorithm’s clarity has slightly short compared with PCA transform. From distortion degree value we found that the improvement algorithm’s value is lower than PCA transform, but higher than wavelet transform. The distortion degree value is small, showed that the fusion image enhanced resolution and retained the image spectrum information well. All the above mean that the improved fusion method achieves basically requests.

5. Conclusion
In this paper, we unified the PCA transform and the curvelet transform and proposed one kind of image fusion method based on PCA and curvelet transform. The experimental results indicated that the new method can strengthen the multi-spectrum image well spatial detail performance ability, and also maintain the multi-spectrum image the spectrum information.

But this method is not the most superior method, it also has some problems. How to improve the algorithm causes the fusion image clarity to enhance again, the distortion degree reduces again and the more retention image's spectrum information will be in the future work consideration.

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