A FUSION ALGORITHM OF HIGH SPATIAL AND SPECTRAL RESOLUTION IMAGES BASED ON ICA

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ABSTRACT:

Independent component analysis (ICA) is a recently developed linear data analysis method. By using ICA method, the correlation and redundancy of multispectral images can be eliminated. In detail, our algorithm can be divided into the following steps (as shown in figure1).Firstly, ICA transform is operated on MS imagery, and then, we get three new independent bands. Secondly, the discrete wavelet transform with linear phrase is used to PAN image and independent components. Then, the rule for combining the ICA coefficients with corresponding wavelet planes of panchromatic band is determined. Finally, inverse ICA is used to get the pan-sharpened image. Compared to other algorithms of RS imagery fusion, our method reduces the data redundancy among MS image bands and also preserves the spectral fidelity of the MS imagery as methods based on wavelet. Experiment result shows that our method can avoid the artifacts in the fused images and fusion result is not sensitive to wavelet decomposition levels.

1. INTRODUCTION

Due to the physical constraint of the spatial information sensors, there is a tradeoff between spatial and spectrum resolution of remote sensing (RS)image (Aiazzi et al., ; Choi). The goal fusing multispectral (MS) low-resolution remotely sensed images with a more highly resolved panchromatic (PAN) image is to obtain a high-resolution multispectral image which combines the spectral characteristic of the low-resolution data with the spatial resolution of the panchromatic image.(Choi, 2006).A fused product used for visual analysis may provide better visual efficiency than the source image, the imagery can also improve the classification accuracy.(Aiazzi et al., ; Choi, ; Hill et al.)

Literature has a large collection of fusion methods, which can be simply classified into several groups. One kind is methods based on color space transformation, including HIS, Lab, YUV and so on. One kind is base on the statistic methods, such as PCA, Brovey transformation etc. Another group of fusion algorithm is based on multi-resolution analysis (MRA) such as pyramid decomposition and wavelet transformation (Aiazzi et al., ; Wang et al.,2005).

Nowadays, the wavelet-based scheme for the fusion of multispectral and panchromatic imagery has become quite popular due to its ability to preserve the spectral fidelity of the MS imagery while improving its spatial quality. But not all kinds of wavelet transform are available for fusion problem. Some shift variance of the transform can lead to artifacts in the fused images. In order to avoid this problem, a novel fusion algorithm combined Independent component analysis (ICA) and wavelet filters with linear phrase was proposed in this paper. The rest part is arranged as follows: in part two, the concept of ICA and a first algorithm are introduced. In the third part, a novel high frequency injection model in ICA domain is proposed. Finally, the experiment result is analyzed in the part 4.

2. ICA AND FAST ALGORITHMS

Independent component analysis (ICA) is a statistical method for transforming an observed multidimensional random vector into components that are statistically as independent from each other as possible, which is proposed by Jutten and Herault in 1991(C and J,1991; C and J,1999). The implication for feature extraction in remote sensing has been found in many works(Zhang et al.,2006).In the simplest way (Comon,1994), the ICA model can be described as follows: there are n unknown statistically independent components $s_1, s_2, s_3, s_4, \cdots s_n$, and theirs linear combinations with m scalar variables $v_1, v_2, v_3 \cdots v_m$ can be observed. That is:

$$v_i = a_{i1}s_1 + a_{i2}s_2 + a_{i3}s_3 + \cdots + a_{in}s_n = \sum_{j=1}^{n} a_{i,j}s_j \quad (1)$$

$$i = 1,2,3 \cdots m$$

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Generally speaking, n is not larger than *m*. if so, principle component analysis is used to reduce dimension from m to n .Then, if we arrange both the observed variables v_i and the component variables s_i into vectors respectively, a matrix form of (1) can be given by

$$v = As \quad (2)$$

Where, $v = (v_1, v_2, v_3 \cdots v_m)^{\mathrm{T}}$, $s = (s_1, s_2, s_3 \cdots s_n)^{\mathrm{T}}$ a nd A is an unknown constant matrix, which is called the mix matrix. Then we can define a demixing matrix *W*, which can be given by:

$$y = Wv \quad (3)$$

Our target is to estimate the independent components s_i from all observed signals alone, which is equivalent to find the optimum estimate matrix *W* in (3), which makes y , the estimate of variables *s*, as statistically independent as possible. Because a linear mixture of Gaussian variables is still a Gaussian variable, at most one source in the mixture model can be allowed to be a Gaussian type.

In detail, the algorithm falls into three steps(陈蜜, 2006). Firstly, the preprocessing step is employed to whiten the mixing data in order to remove the correlation between variables and reduce data dimension (if necessary).Secondly, a subjective function $L(W)$ using the demixing matrix *W* as argument is defined to measure the independence of output variables y .Finally, a optimization algorithm is used to find a optimal estimation $\hat{W}$,which makes $L(W)$ has the extremum, while W is equal to $\widehat{W}$. The implementation of ICA can be seen as a combination of a objective function and a optimization algorithm(Hyvärinen,1999). The key point of algorithm is the definition of statistical impendence. In general, there are three kinds of objective functions: the maximum of non-gaussianity, the minimum of mutual information and maximum likelihood.

It has been improved that three criterions are equal to each other in the term of information's(Hyvärinen,1997),the difference between them is laying in the optimization algorithm, which means different calculating complexity. For non-gaussianity, kurtosis and negentropy are often used as performance criterion. For a random variable y with zero mean, its kurtosis can be defined as follows:

$$kurt(y) = E\{y^4\} - 3(E\{y^2\})^2 \quad (4)$$

Meanwhile, its negentropy is presented in (6), which is the difference between the entropy of a gauss rand variable that is same as y in standard deviation and the entropy of y .

$$H(x) = -\sum_i P(x = a_i) \log P(x = a_i) \quad (5)$$

$$ne(y) = H(y_{gauss}) - H(y) \quad (6)$$

A large collection of literature on optimization algorithms have been proposed in the last ten years. Among them, a fast and robust ICA (Fast-ICA) algorithm proposed by Hyvarinen (Hyvärinen, 1997) is widely used, which is a fixed-point algorithm based on an minimum of negentropy. Initially, this algorithm is introduced using (6) as a criterion function, and is subsequently extended into function (7) in order to reduce complexity of computation.

$$ne(y) = [E\{G(y)\} - E\{G(v)\}]^2 \quad (7)$$

$$y = w^T x \quad (8)$$

In which, v is a Gaussian variable of zero mean and unit variance and y is a variable of zero mean and unit variance. Function $G(\bullet)$ can be practically any non-quadratic functions. Two commonly used functions are listed below:

$$G_1(y) = \frac{1}{a} \log \cos(a_1 y) \qquad a_1 \in [1,2]$$

$$G_2(y) = -\exp(-y^2/2)$$

In our experiment, $G_2(y) = -\exp(-y^2/2)$ is used for iteration. Our target is finding an appropriate value for vector w in order that $E\{G(w^T x)\}$ has a maximum, which is equivalent that the deviation of $E\{G(w^T x)\}$ is equal to 0. In formula (7), $g(\bullet)$ is the deviation of $G(\bullet)$

$$E'\{G(y)\} = E'\{Gxg(w^T x))\} = 0 \quad (8)$$

According to Newton Iteration algorithm, we can get iteration method simplifies to:

$$w^+ = w - \frac{E\{xg(w^T x)\}}{E\{g'(w^T x)\}}$$

Then we get following fixed-point algorithm for ICA:

1. Take a random initial vector w of norm 1.
2. Let $w^+ = -E\{g'(w^T x)\}w + E\{xg(w^T x)\}$
3. Divide w^+ by its norm, then get a new w .

4. If new w is close enough to w^{+}, output the vector w .Otherwise, go back to step2.

3. MULTIRESOLUTION DATA FUSION BSAED ON ICA

The different bands in remote sensing imagery have strong correlated, which is caused by some interference factors such as weather, atmosphere condition, etc. On other hand, the established models for ground object imaging have no enough refutation accuracy under some uncertain disturbed conditions. So we use ICA to remove the interference, and get an independent representation of original bands. Then the high frequency information extracted by discrete wavelet transform. Considering the high frequency of the image is compared to detail part and the low frequency is corresponding to the profile part of the image roughly. In our method, the high frequency elements in every scale are replaced by the corresponding part of the panchromatic frequency bands. Then, reconstruction is performed for three multispectral band and we get finally fusion result by inversing ICA transform. The diagram on the whole process can be found in Fig1.

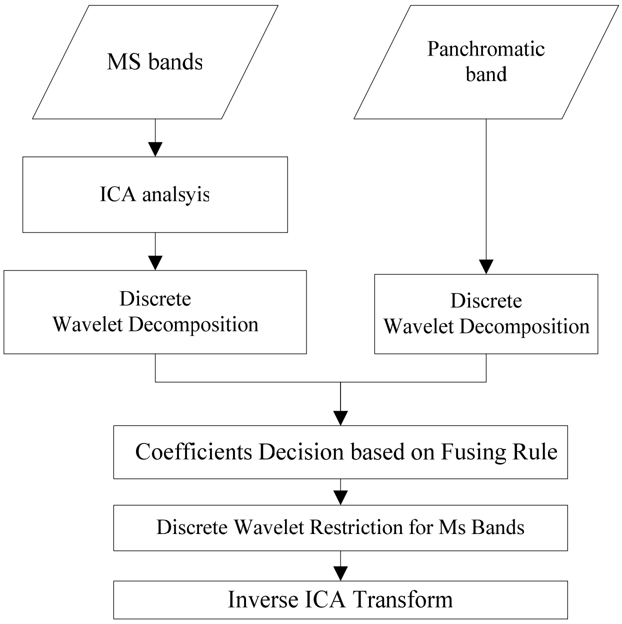
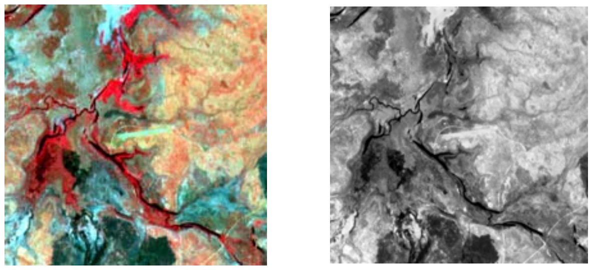


Fig.1 the fusion diagram

In detail, three multispectral bands are firstly changed into three vectors R, G, B. Then the fast ICA algorithm mentioned above is employed to get three independent components, IC1, IC2, IC3. In formula 9, F means an ICA operation.

$$[IC1, IC2, IC3] = F(R, G, B) \quad (9)$$

Thirdly, the discrete wavelet decomposition is applied on the panchromatic band P and three independent components. As mentioned in the section 1, only part of wavelet base can be used in the fusion procedures to avoid or reduce the artefacts. In our experiments, Coiflet bases with different orders, which have



a. original image (512×512) b. synthesized P band (512×512)

Fig.2 Landsat-P synthesized from three B1, B2, B3 as P = (B1+B2+B3)/3

a. l multispectral image (128×128) b.panchromatic band (512×512)

Fig 3 Quick bird image used for fusion

linear phrase is compared. This procedure can be expressed as follow formula 10, 11.

$$\begin{aligned} IC1 &= \sum_{i=1}^{n} h_l^{IC1} + \sum_{i=1}^{n} h_V^{IC1} + \sum_{i=1}^{n} h_d^{IC1} + a_n^{\ IC1} \\ IC2 &= \sum_{i=1}^{n} h_l^{IC2} + \sum_{i=1}^{n} h_V^{IC2} + \sum_{i=1}^{n} h_d^{IC2} + a_n^{\ IC2} \\ IC3 &= \sum_{i=1}^{n} h_l^{IC3} + \sum_{i=1}^{n} h_V^{IC3} + \sum_{i=1}^{n} h_d^{IC3} + a_n^{\ IC3} \end{aligned} \quad (10)$$

$$P = \sum_{i=1}^{n} h_l^{P} + \sum_{i=1}^{n} h_V^{P} + \sum_{i=1}^{n} h_d^{P} + a_n^{\ P} \quad (11)$$

Where, n is the number of decomposition levels. In the above equations, h_l^P, h_v^P , and h_d^P represent the detail images of the PAN image at successively higher scales n, while a_n^P is the approximation image. The detail and approximation images of the ***IC1,IC2, and IC3*** images can be understood similarly.

Because panchromatic band is rich in spatial information, and structure spatial is mainly concentrated on wavelet planes. A substitute fusing algorithm can be deduced. (as shown in formula 12.)Finally, fusion result can be got by inverse ICA transform (In formula 13).

$$IC_1' = \sum_{i=1}^{n} h_l^P + \sum_{i=1}^{n} h_V^P + \sum_{i=1}^{n} h_d^P + a_n^{IC1}$$

$$IC_2' = \sum_{i=1}^{n} h_l^P + \sum_{i=1}^{n} h_V^P + \sum_{i=1}^{n} h_d^P + a_n^{IC2} \qquad (12)$$

$$IC_3' = \sum_{i=1}^{n} h_l^P + \sum_{i=1}^{n} h_V^P + \sum_{i=1}^{n} h_d^P + a_n^{IC3}$$

$$[R', G', B'] = F^{-1}(IC_1', IC_2', IC_3') \qquad (13)$$

4. EXPERIMENTAL RESULTS AND COMPARISONS

4.1 Synthetic Datasets and Real MS-PAN Datasets

The main aim of this research is to determine the efficiency of new algorithm based on ICA for merging images with a particular resolution ratio. Due to the difficulties in obtaining adequate imagery with particular ration, Yocky's approach (Yocky, 1996)is employed to synthesize some MS-PAN datasets with particular ratio. In this approach, a Landsat TM test image was available in the three bands,i.e., B1 (green), B2 (red), and B3 (near infrared). The image was used to synthesize a perfectly overlapped panchromatic band at 20 m, which is shown in fig2.

4.2 The Quality Analysis of the Fusion Image

We have adopted some quantification metrics to evaluate the fusion quality, including entropy, mean, and standard deviation，Average gradient. Among these metrics, entropy explores the information changes, and an image has more information when the entropy is bigger. And some other metrics, such as mean, employed to evaluate the aberrance of the spectral information. The mean calculates the degree of the spectral information change. In our research, different decomposition levels for wavelet have been tested. Limited by space, only the result for true data set is show in Fig 4.

For visual analysis, we could find that our method can enhance the image spatial resolution to a certain degree, which will benefit those applications which are demanding strictly on the

a. original MS bands(128×128)

b. 2 level

c.3 level

d.4 level

Fig 4 he fusion result with different decomposition levels for true data size(512×512)

details of an image, such as image interpretation, special cartography, and photogrammetric survey, etc. With decomposition level increasing, more panchromatic band information is injected into three multispectral bands and gray levels of images seems no demonstrate change, which means that our method may be not sensitive to wavelet decomposition level.The synthesized data has shown the same trend. So when we consider the computation efficiency, the less decomposition level such as 2 or 3 is preferable. We have also adopted some quantification metrics to evaluate the fusion quality. The statistical data for true data is shown in table1. It can be included from tables: the information in both of the two datasets is increased in the case of the injection of the information .Because the high frequency information in the multispectral bands is substituted by the corresponding parts in the panchromatic band. However when decomposition level increased, the result had no demonstrable change. It means that our method is not sensitive to decomposition level as tradition MRA based method. So we proposed a useful fusing algorithm.

Metrics	Band	Original spectral bands	2	3	4
Mean	R	113.59	113.23	113.23	113.20
	G	100.23	99.87	99.87	99.84
	B	93.85	93.42	93.42	93.45
Standard deviation	R	73.50	74.10	74.09	73.78
	G	70.51	73.27	73.28	72.49
	B	70.65	69.44	69.44	69.71
Average gradient	R	14.57	21.97	21.97	21.71
	G	14.66	20.15	20.15	17.57
	B	14.39	16.21	16.21	17.38
Entropy	R	4.97	7.90	7.90	7.9
	G	4.94	7.83	7.83	7.85
	B	4.85	7.80	7.80	7.80

Table.1 statistical data for true MS-PAN dataset

5. CONCLUSION AND PROSPECTS

A new multispectral and panchromatic band merging method is provided by combining ICA transform with discrete wavelet. The experiment result shows that the method can improve the spatial information of original spectral bands effectively. But spectral distortion is still a problem in fusion result. In the future, our work is focused on establishing a more flexible fusion rule for information displacement.

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