A Remote Sensing Image Fusion Algorithm Based on Ordinal Fast Independent Component Analysis

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Abstract

Data fusion on remote sensing is hot in current image processing. A new approach, that is the ordinal fast independent component analysis for remote image fusion between Landsat ETM+ panchromatic and CBERS multi-spectral images, is proposed to eliminate high-order image data redundancy for two different Remote sensing images. The independent components are done factor analysis, and then the fused image is obtained by applying image fusion rule. Visual and statistical analysis proves that the concept of fusion based on the ordinal fast independent component analysis is promising, and it significantly increases the signal-to-noise ratio and improves the fusion quality.

1. Introduction

With the development of modern remote sensing technology, the spatial and spectral resolution of remote sensors has been greatly improved which leads to the diversity and complexity of data sources. The data fusion is an important tool for improving the data quality in remote sensing and can effectively integrate the images from different sources into one image. The image fusion techniques have become a hot problem in recent years [1-3].

Traditional image fusion methods in the remote sensing contain the intensity-hue-saturation (IHS) transform, principal component analysis (PCA), discrete wavelet transform (DWT) and etc. [4]. Although these methods improve the quality of the fusion result, there are still some limitations. For example, these fusion algorithms do not eliminate redundancy between different data, or just eliminate the low-order data redundancy, and do not consider the higher-order statistical properties of the signal [5].

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In this paper, to overcome these limitations, we propose a new image fusion algorithm for Landsat ETM+ and CBERS images. The new fusion method is ordinal fast independent component analysis (ICA). Experimental comparison with conventional fusion methods shows that the ordinal fast independent component analysis fusion method outperforms these existing approaches.

2. Independent Component Analysis

The traditional fusion methods including IHS, PCA and DWT are all based on spatial or frequency domain which does not consider redundancy between the different signals. Although the PCA method could eliminate the low-order redundancy, it does not take the high-order redundancy into consider. According to the statistical theory, the most important information of image signal is always included in the statistical characteristics of high-order [6].

Therefore, a new fusion method is proposed which is ICA. ICA which is recently developed from blind source separation is a novel high-order statistic signal processing method and it tries to transform an observed multidimensional vector into components that are statistically as independent from each other as possible [7-9]. In remote sensing image fusion, ICA is very useful and gradually become a hot problem in signal processing.

ICA is signal processing technique whose goal is to express a set of random variables as linear combinations of statistically independent component variables. The estimation of the data model of independent component analysis is usually performed by formulating an objective function and then minimizing or maximizing it. Therefore, the properties of the ICA method depend on both of the objective function and the optimization algorithm. Assume that there is an M-dimensional zero mean vector $s=(s_1,s_2,...,s_M)^T$, whose components are mutually independent. The vector $s(t)$ corresponds to n independent scalar valued source signal s_i . A data vector $x=(x_1,x_2,...,x_N)^T$ is observed vector at point t, such that

$$x(t) = As(t) \quad (1)$$

Where A is an N*M scalar matrix which is called mixing matrix.

Sometimes we need the columns of matrix A, if we denote them by a_j the model can also be written as,

$$x = \sum_{i=1}^{n} a_i s_i \quad (2)$$

The estimation of data model of independent component analysis usually chooses a suitable objection function and then minimizes or maximizes it. we use fast independent component analysis (fast ICA) algorithm. The fast ICA is based on a fixed-point iteration scheme for finding a maximum of the non-Gaussianity, with a fast convergence rate. The algorithm using Newton iterative algorithm, is very efficient method of maximization with the negative entropy as the objective function.

It is here assumed that the data is preprocessed by centering and whitening. Fast ICA algorithm finds a direction by system study, which is cell vector w , makes its projection $w^T z$ have the maximal non-Gaussianity. It is an algorithm that maximizing the non-Gaussianity of $w^T z$ based on fixed-point iteration. The left side of the equation is assumed to be F, and the gradient of the F as

$$\frac{\partial F}{\partial w} = E\{zz^{\mathrm{T}}\, g'(w^{\mathrm{T}} z)\} + \beta I \quad (3)$$

To simplify the transpose of the matrix, the first term of the above formula is approximated to the following formula because the data has been normalized.

$$E\{zz^{\mathrm{T}} g'(w^{\mathrm{T}} z)\} \approx E\{zz^{\mathrm{T}}\} E\{g'(w^{\mathrm{T}} z)\} = E\{g'(w^{\mathrm{T}} z)\} I \quad (4)$$

The above formula can be further simplified as below:

$$w \leftarrow E\{z\, g(w^{\mathrm{T}} z) - E\{g'(w^{\mathrm{T}} z)\}\, w\} \quad (5)$$

The above conclusion is for one independent component, and if we want to estimate more than one unit, we must use the symmetric approach of Fast ICA and then we can get the independent components at the same time.

We introduce the fast ICA method into remote image fusion to separate the different spectrum information. The approach is based on the assumption that the spectrum information of different remote images is separated and the resolution of images is m × n. We can see the multi-spectra image with bands 1, 2 and 3and panchromatic image as a random matrix of 4 × (m × n), so that the observed signals is $x=[R,G,B,P]^T$, here, R, G, B respectively corresponding to the three bands of multi-spectral image, P stands for the panchromatic image. Therefore, we can obtain independent components by ICA model and fast ICA algorithm, denote $s=[\mu_1, \mu_2, \mu_3, \mu_4]^T$.

3 The Improvement of ICA's Ambiguities

In the ICA model, we cannot determine the order of the independent components. The reason is that, again both s and A being unknown, we can freely change the order of the terms in the sum in equation (2). Formally, a permutation matrix P and its inverse can be substituted in the model to give $x = AP^{-1}Ps$. The elements of Ps are the original independent variables s_j, but in another order. The matrix AP^{-1} is just a new unknown mixing matrix, to be solved by the ICA algorithms. Therefore, the Ordinal fast ICA algorithm uses factor analysis methods to obtain unique ICs.

The basic idea of factor analysis is group by the correlation of variable, so that the variable in the same group has higher correlation, but in different group with lower correlation. Each group represents a basic structure, are called factor.

Assume a random vector x with p dimension, the mean of it is μ , covariance is $\sum$. The factor analysis model is as equation (6).

$$X = \mu + Lf + \varepsilon \quad (6)$$

Where $f_1, f_2, ... f_m$ is mutual factors and $\varepsilon_1, \varepsilon_2, ... \varepsilon_p$ is specific factors or error, $L = (l_{ij})_{p\times m}$, The elements l_{ij} of matrix L are called factor loadings.

To establish factor model, first we should estimate factor loadings matrix and special variance. Then, look for a reasonable interpretation of the factors. Therefore, the two components which contribute most to the same common factor can be seemed as the corresponding components.

In our experiment, we have a new matrix owned 8 vectors. The former four vectors are observed signals and the latter four vectors are independent components. We do factor analysis to get 4 common factors. The rotated component matrix is as table 1.

Table 1 the rotated component matrix

	Component			
	1	2	3	4
V1	-.193	.521	.831	.040
V2	.869	.224	.340	.281
V3	.903	.218	.333	-.162
V4	.063	.990	.101	.082
V5	.020	.030	.006	.999
V6	-.940	.122	.319	.013
V7	.146	.987	.054	-.033
V8	.308	-.098	.946	-.009

From table1, we can conclude that the fourth component is the estimate of the first original signal, the first component is the estimate of the second original signal, the second component is the estimate of the third original signal, the third component is the estimate of the fourth original signal. The result is consistent to the eyeballing result. Factor analysis can eliminate indeterminacy of ICA results.

4 Basic idea of ordinal fast Independent Component Analysis fusion method

To eliminate high-order image data redundancy for two different Remote sensing images, we introduce ordinal fast independent component analysis for remote image fusion between Landsat ETM+ panchromatic and CBERS multi-spectral images. The images after ordinal fast independent component analysis as a new tool for image fusion both could improve spatial resolution and preserve spectral characteristics. The detailed steps of this integrated fusion method are as follows, first, registering the multi-spectral image and the panchromatic image with the error in a pixel, and denoting by $x=[R,G,B,P]^T$. Then we obtain the independent components by fast ICA, with it denoting by $s=[\mu_1,\mu_2,\mu_3,\mu_4]^T$. As the factor analysis can eliminate indeterminacy of ICA results, we do factor analysis to get 4 common factors. Next, find an effective fusion rule for fusion. The detailed fusion rule is as follows:

$$\lambda_1=(\lambda_1+\lambda_4)/2 \tag{7}$$

$$\lambda_2=(\lambda_2+\lambda_4)/2 \tag{8}$$

$$\lambda_3=(\lambda_3+\lambda_4)/2 \tag{9}$$

Where, we assume the independent components λ_1、λ_2、λ_3、λ_4 are the estimate of observed signals $x=[R,G,B,P]^T$ sequentially. At last, the fusion image is obtained by inverse fast ICA.

The process of image fusion is shown in Fig1.

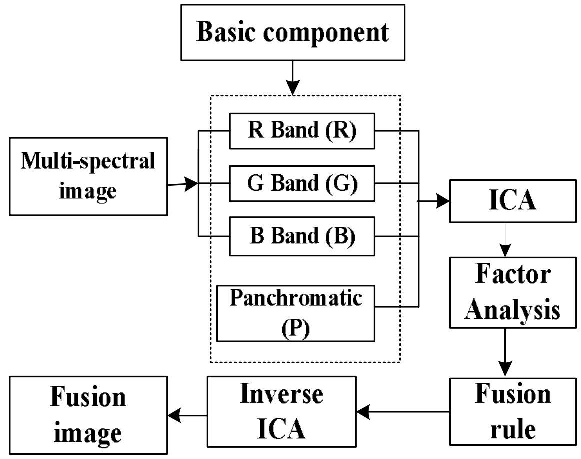
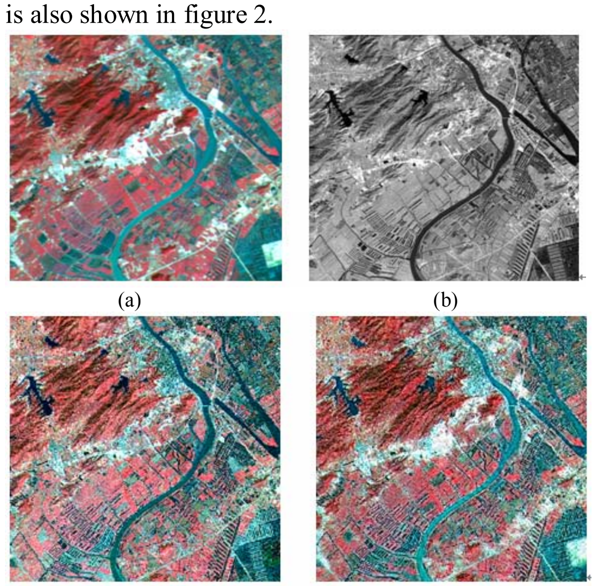


Fig. 1.Processing flow of the ordinal fast independent component analysis fusion method

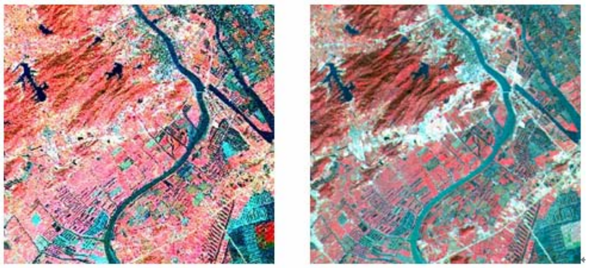
5 Experiments and Evaluation

The study area is located in the urban area of Zhuhai, China. Fig. 2(a) shows a CBERS multi-spectra image with bands 1, 2 and 3, acquired in 2001.Fig. 2(b) shows the ETM+ panchromatic image, acquired in 1999.A scene of 256 × 256 pixels in size was selected for our experiments, and it includes some ground covers, such as the area for agriculture, forest, grass, man-made infrastructure and etc. Experimental results compared with those of conventional fusion methods including IHS transform [10], PCA [11] and DWT [12] is also shown in figure 2.



(a) (b)

(c) (d)



(e) (f)

Fig.2 The original remote sensing images and the fused results: (a) original CBERS multi-spectral image with bands 1, 2 and 3; (b) Original ETM+ panchromatic image; (c) fusion result based on IHS transform; (d) fusion result based on DWT(5/3) transform; (e)fusion result based on PCA; (f) fusion result based on ordinal fast independent component analysis.

To assess the quality of the fused images, this experimental use the signal-to-noise ratio（PSNR） as statistical parameter to evaluate the effect fusion result. The quantitative results of different fusion method are shown in table 2.

Table 2 the contrast between different fusion results

band	PSNR			
	IHS	DWT	PCA	Fast-ICA
R	14.5890	16.4525	11.3327	20.9196
G	13.8819	15.3591	11.3741	19.9235
B	13.8548	15.0530	11.4700	20.0556

The PSNR is used to measure the difference between images. By analyzing and comparing the all fusion methods from statistical parameters (table 2) and visual measurements (figure 2), we can draw conclusions that, the ordinal fast independent component analysis fusion method produce better result with higher PSNR. From visual measurements aspect (figure 2), the same conclusion can be drawn. In other words, the images after ordinal fast independent component analysis as a new tool for image fusion both could improve the quality of fusion image.

6. Concluding Remarks

ICA is a novel method for finding underlying components from multivariate statistical data. To eliminate high-order image data redundancy for two different remote sensing images, we propose a new method that is ordinal fast independent component analysis for remote image fusion between Landsat ETM+ panchromatic and CBERS multi-spectral images. At the same time, we use factor analysis to determine the sequence of ICA results. After applying the effective fusion rule, we can get more exact results. Experiments show that compared with those of conventional methods, ordinal fast independent component analysis fusion method produces better fusion result.

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