STUDY ON INDEPENDENT COMPONENT ANALYSIS' APPLICATION IN CLASSIFICATION AND CHANGE DETECTION OF MULTISPECTRAL IMAGES

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ABSTRACT:

Image classification and change detection is a hot topic in remote sensing. This paper sought to apply the method of independent component analysis (ICA), which develops from blind source separation, to multi-spectral image classification and change detection. In this paper, we firstly introduced the principle of ICA, especially the Fast-ICA algorithm. Then a Fast-ICA based image classification algorithm was proposed. Using this algorithm we made transformation on the original image and extracted some thematic information such as vegetation, water body in advance, thus gave facilities for the next classification. Next a new change detection model based on Fast-ICA was presented. The two components from ICA transformation represent background image and changed image respectively. From the latter component we could extract changed areas easily. Finally, we carried this method on two dates ETM+ images of the same area. The experiment results showed that this approach is efficient and effective.

1. INTRODUCTION

Image classification has been one of the hottest issues in remote sensing and its related fields. Many scholars have been searching for a method of fast, high-accuracy automatic classification. With the requirements of categories in classification increasing, the probabilities of wrong classification are increasing too. If we could separate out certain types of pixels in advance, and then classify the remaining pixels, we can reduce the probabilities of mistakes effectively and improve classification speed.

Image change detection has been applied in many aspects of international economy and demonstrated its superiority. It has become a hot research in current international remote sensing field. Due to the complexity of the issues, there has not yet a unified solution for image change detection. Current methods require different image preprocesses, and the ability and accuracy to detect changes is also limited. Traditional methods such as PCA difference and ratio transformation need repeated tests to choose a threshold for pixels change detection.

Independent Component Analysis (ICA), orienting as an efficient approach to the blind signal separation problem, attempts to make the separated signals independent from each other as much as possible. It is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA is based on higher order statistics and decorrelates the input signals as well as making the result signals independent from each other. It is applied in biomedicine signal processing, error diagnose, sound signal separation, feature extraction etc[1]. Though ICA has a wide range of applications in the current signal processing fields, its applications in image processing, especially in remote sensing image processing, is relatively less[2].

In this paper, we firstly expounded on the principle of ICA, especially the Fast-ICA algorithm, and then ICA transformed the original three bands of ETM+ sensor. From the three independent components coming from this transformation we could extract some thematic information easily. These extracted ground types were then removed from the original image for the next classification. Next, a Fast-ICA based change detection model was proposed. Finally, we applied this method to two dates ETM+ images of the same area, and compared its results with traditional methods such as PCA difference and ratio transformation. It came to the conclusion that this approach is efficient and effective.

2. RELATED WORK

Several effective image classification algorithms have been proposed in recent years, e.g., artificial neural network (ANN) methods, decision tree classification, pixel-based classifiers, object-oriented classifiers and so on. Neural network has more flexible requisitions for data and higher tolerant degree. In multi-source classification, where we do not always know the distribution functions, NNs can be more appropriate than statistical algorithms. For example, Fabio Del Frate and Fabio Pacifici used neural networks for automatic classification from high-resolution images[3]. Decision trees are commonly used in image analysis for variable selection, to reduce data dimensionality and to incorporate ancillary information[4]. Classification accuracies of decision tree classifiers are often greater compared to using maximum likelihood or linear discriminant function classifiers[5]. Pixel-based classifiers have difficulty in dealing with the spectral variations in tree crowns, as was indicated in a study[6]. Recently, object oriented classification methods such as those offered by eCognition

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professional have been embraced because a pixel no longer represents a single object, but rather a component of an object[7]. Object-oriented classifiers allow users to treat a crown as one object. Kristof, Csato and Ritter[8] used 1m panchromatic and 4m multi-spectral IKONOS imagery and an object oriented classification scheme to classify a forest in Hungary.

With the development of remote sensing technology in recent years, a number of change detection methods have been proposed, such as image difference, ratio transformation, post-classification comparison, normalized difference vegetation index and change vector analysis(CVA). The use of ICA features for unsupervised signature extraction of IKONOS images has been investigated previously[9]. In remote image classification, Zeng Shenggen proposed a modified Fast-ICA (M-FastICA) algorithm. Compare to basic Fast-ICA algorithm, M-FastICA runs fast and has better convergence performance, and improves the validity of the ICA in classifying of the remote sensing images[10]. In the field of image fusion, Li Xiaochun proposed a fusion algorithm for multi-temporal images based on ICA and change detection. The algorithm can effectively embody contour and detailed structure of objects' in both images[11].

Based on the aforementioned work, in this paper, we will test and verify the effectiveness and advantages of Fast-ICA algorithm in multi-spectral image classification and change detection. The paper is organized as follows: we begin with an overview of various effective image classification and change detection methods in recent years. In section 3, an overall structure of fast-ICA based image classification and change detection algorithm is illustrated. Section 4 shows the experiment results of this algorithm and section 5 comes to the conclusions.

3. FAST-ICA ALGORITHM BASED IMAGE CLASSIFICATION AND CHANGE DETECTION

3.1 Definitions of linear ICA and Fast-ICA algorithm

Independent Component Analysis (ICA) is a statistical technique for decomposing a complex dataset into independent sub-parts. It develops from blind source separation and tries to transform an observed multidimensional vector into components that are statistically independent from each other as much as possible. There are at least three different common used definitions for linear ICA.

Definition 1: ICA of the random vector X consists of finding a linear transform S=WX so that the components S_i are as independent as possible, in the sense of maximizing some function $F(S_1,\ldots,S_m)$ that measures independence.

Definition 2: ICA of a random vector X consists of estimating the following generative model for the data:

$$X = AS + n \tag{1}$$

Where X is the vector of observed signals and n is a random noise vector. The matrix A is the mixing matrix to be estimated, and S is the mutually independent components.

Definition 3: Noise-free ICA model is as follows:

$$X = AS \tag{2}$$

where matrix A and S are the same as in Definition 2. In this paper, we will concentrate on this definition.

There are many algorithms for performing ICA, but the most efficient to date is the FastICA algorithm which was proposed by Hyvarinen[12], it is a fixed-point algorithm based on an optimization of entropy function called negative entropy. Unlike PCA, ICA can be seen as a tool based on higher order statistics, and it not only decorrelates the input signals but also makes the result as independent as possible. Fast-ICA algorithm is based on the negative entropy of the input signal to measure its non-Gaussian. The algorithm running quickly for objective function optimization, and has good stability. Figure 1 shows the Fast-ICA model.

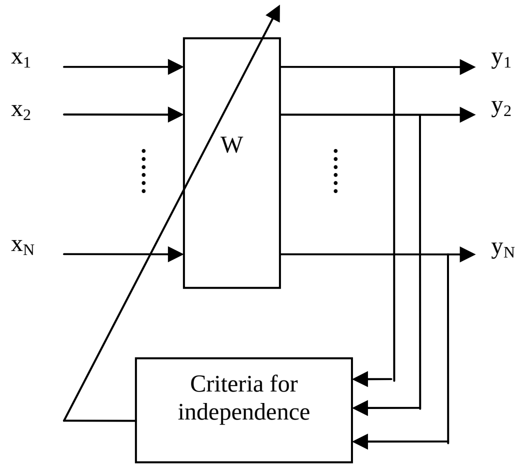

Figure 1. Fast-ICA model

According to the approximate calculation of negative entropy we get following commonly used objection function:

$$J_G(\mathbf{w}_i) = [E\{G(\mathbf{w}_i^T\mathbf{x})\} - E\{G(v)\}]^2 \tag{3}$$

Where $y_i = \mathbf{w}_i^T\mathbf{x}$ and w is an m-dimensional vector constrained such that $E\{(w^T x)^2\} = 1$, v is a Gaussian random variable of zero mean and unit variance. $G(y_i)$ is a nonquadratic function. In order to achieve signal separation, we need only under restrictive conditions that

$E\{(\mathbf{w}_k^T\mathbf{x})(\mathbf{w}_j^T\mathbf{x})\} = \delta_{jk}$ to maximize $\sum_{i=1}^{N} J_G(\mathbf{w}_i)$.

3.2 Fast-ICA based image classification and change detection

3.2.1 Image classification

Assuming that the composition of each mixed pixel is a random variable (i.e. a random signal source), and the spectral response curves of ground types are independent from each other. Each spectral response curve constitutes a source signal, and the multi-spectral image can be considered as a mixed-signal of these source signals. Thus the classification of the multi-spectral image become into a mixed-signal's blind source separation issue, and this just meet the mathematical model of ICA.

The steps of using Fast-ICA algorithm for multi-spectral image classification are as follows:

(1) Centering the input image bands, that is, the observation signal x;
(2) Whitening the centered signal x;
(3) Initializing weight vector w, and set convergence error ε ;
(4) Updating weight vector w. Using following iterative formula that added step- size μ to improve stability.

$$w_i^+ = w_i - \mu[E\{xg(w_i^T x)\} - \beta w_i] / [E\{g'(w_i^T x)\} - \beta] \quad (4)$$

where $\beta = E\{\mathbf{w}_i^T \mathbf{x} g(\mathbf{w}_i^T \mathbf{x})\}$. The step-size μ is changed adaptively;

(5) Normalizing weight vector w: $w_i^+ = w_i^+ / \|w_i^+\|$;

(6) If $|w_{k+1} - w_k| > \varepsilon$, algorithm is not reach convergence, repeat steps (4) and (5);

(7) If the algorithm did not converge and iteration exceeds the pre-set greatest number(for example 100), half the step-size and back to (4) and (5) until $|w_{k+1} - w_k| < \varepsilon$;

(8) Get the separation matrix w and ICA transform original image, and extracting thematic information from ICA components.

3.2.2 Image change detection

The theory of ICA algorithm for change detection is based on subspace projection method. For two random variables $x1$ and $x2$, if we could estimate the independent component $s1$ of $x1$, then we could project $x2$ to $s1$. Assuming the projected signal is $x2'$, in this way the difference value of $x2'$ from $x2$ is the changed value of $x2$ relative to $x1$.

It may be assumed that the subspace of $x1$ as a component: background image and the different strength of changed pixels as another component: value changed image. The two components are independent from each other. In image change detection, two temporary images can be computed from these two components through a linear mixed transformation. That is, in the ICA model, the two images from different date comes into the input mixed signals, and the background image and pixel value changed image constitute two independent source signals.

As the actual remote sensing images have multiple bands, it is not convenient for ICA processing. Considering PCA transformation can be used in data compression, and information from the first PCA component is the most abundant (under normal circumstances to achieve more than 90 percent of the source multiple bands image), so we firstly PCA transformed the multi-spectral two dates images. Then we got their first principal components. In this way, the first principal components can be considered to be the input mixed signals of ICA transformation. After ICA transformation we got two independent components: component one represents the unchanged background and component two the changed area. Based on component two, using threshold 255 we could extracted the changed areas easily.

The algorithm processes are as follows:

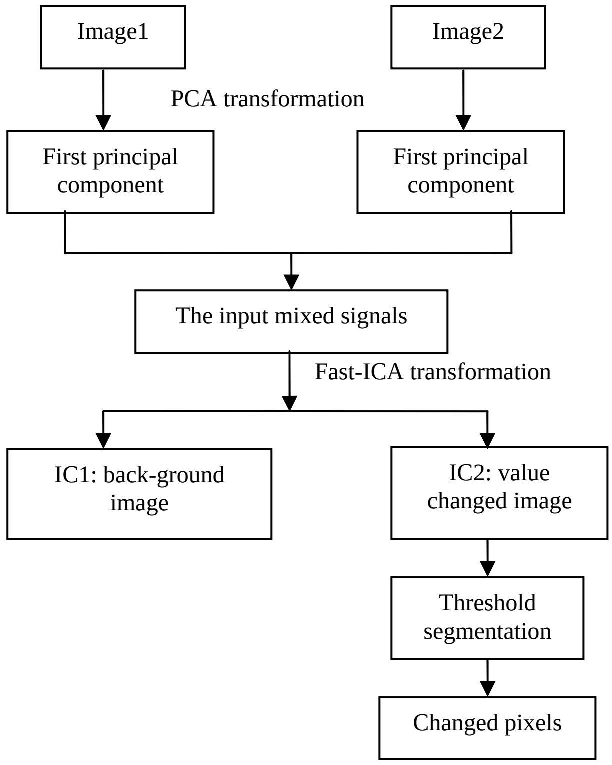

Figure 2.Fast-ICA based image change detection model

4. EXPERIMENT RESULTS

The study area locates in ZhuanKou district, Wuhan city. The two ETM+ images are acquired in the year of 1999 and 2000 respectively, and the bands used are band3, band4 and band5. Pre-processing the image with centering and whitening, then the three bands are used as input signals for ICA transformation. We firstly used ICA algorithm for image classification of the year 2000, to certify the feasibility and effectiveness of this algorithm. Then we used the above change detection model to detect changed areas between these two years. The experiment results are shown as follows:

Figure 3. ETM+ images of 1999 and 2000

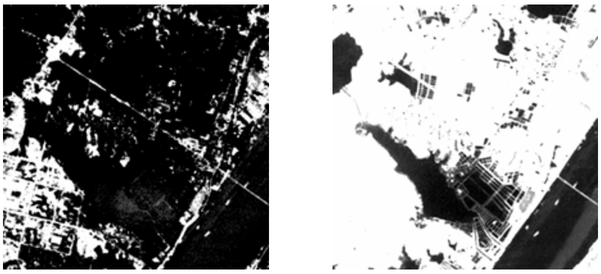

Figure 4. Independent components (IC1, IC2) of 2000 image

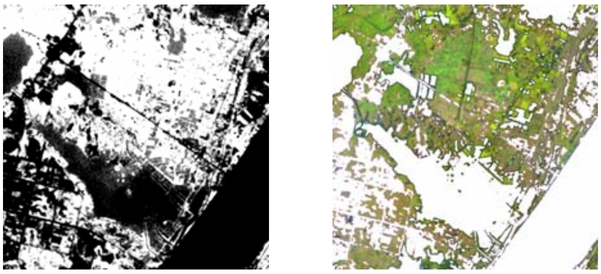

Figure 5(a). IC3 of 2000 image Figure 5(b). remaining pixels after removing IC1 and IC2 extracted categories

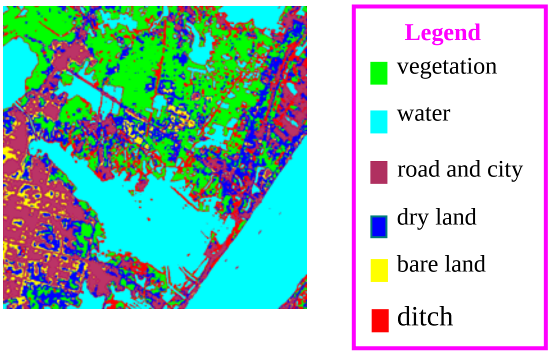

Figure 6. ICA-based classification result (2000)

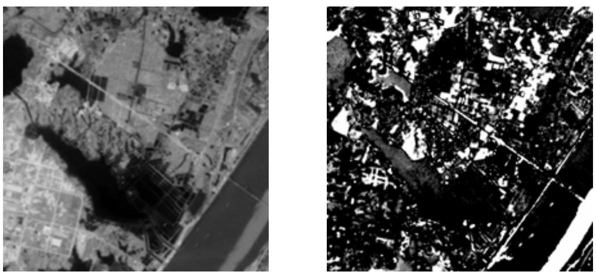

Figure 7. ICA-based change detection: background image IC1 and value changed image IC2

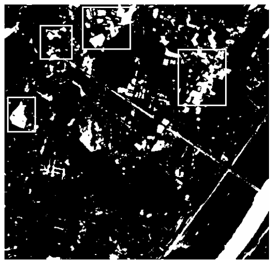

Figure 8. Changed result based on value changed image IC2: threshold (255)

Figure 3 are the original ETM+ images of 1999 and 2000. Figure 4 and 5(a) are the three independent components from ICA transformation. We can see that IC1 separated out city and road from other categories obviously, and IC2 gave a very obvious display of water body. Based on these two independent components, using threshold 255, we can separate out these two types from other objects. Then we removed them from original image and classify the remaining pixels. The last classification result is shown by Figure 6. Figure 7 is the two independent components of ICA-based change detection: the background image that represents unchanged area and the changed pixels. Based on the latter component, using threshold 255 we can extract the change area easily. Figure 8 shows the last change detection results.

From the two original images, the main changed areas are the following:
(1) On the left upper corner, there is no crossroad on the junction of two roads on the former image, while it exists on the latter image.
(2) On the middle left part, a bare land on the former image changed into concrete road.
(3) The Baisha Island in Yangtze River could be seen on the right lower corner on the former image while it disappeared on the latter one.
(4) On the middle upper part, some water body on the former image changed into vegetation.

From the experiment result we can see that these main changed areas have been extracted using the method proposed by this paper, as shown in the white box on Figure 8. Meanwhile, Error matrix is used to evaluate detection accuracy quantitatively. Comparing and analyzing land use investigation in 1999 and 2000, we can obtain 29850 changed pixels and 232294 unchanged ones in the image, which are used to test the accuracy of this application, as Tab.1 shows. The application reach 97.70% overall accuracy and consistent coefficient Kappa is 0.887. The assess result demonstrates the ability of this method is effective and efficient.

data	test data			
	changed pixels	unchanged pixels	sum	user's accuracy/ %
changed pixels	27171	3342	30513	89.05
unchanged pixels	2679	228952	231631	98.84
sum	29850	232294	262144	
producer's accuracy/ %	91.03	90.82		
Overall accuracy = 97.70%			Kappa = 0.887	

Table 1. Error matrix of changed/unchanged area s

5. CONCLUSIONS

This paper studied on independent component analysis' application in classification and change detection of multi-spectral images. The thematic information extracted from independent components is very useful for the remaining pixels' classification and ICA-based change detection can extract most mainly changed areas. The experiment results certified the feasibility and effectiveness of using ICA in image classification and change detection. However, in this paper we mainly discussed the application of ICA in classification and change detection but didn't compare it to other methods, we will investigate this in the near future.

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