IMAGE FUSION BASED ON EXTENSIONS OF INDEPENDENT COMPONENT ANALYSIS

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ABSTRACT:

Remote sensing image fusion can effectively improve the accuracy of image classification. This paper proposes an image fusion algorithm based on extensions of independent component analysis (ICA) and multi-classifier system. Firstly a novel method of fusing panchromatic and multi-spectral remote sensing images is developed by contourlet transform which can offer a much richer set of directions and shapes than wavelet. As ICA not only can effectively remove the correlation of multi-spectral images, but also can realize sparse coding of images and capture the essential edge structures and textures of images, then using features extracted from the extension of ICA domain coefficients of the fused image, different classifiers corresponding to different image features are chosen in parallel style and the support vector machines are trained to classify the whole fused image as stack part in the proposed multi-classifier system. Experimental results show that the proposed algorithm can effectively improve the accuracy of image classification.

1. INTRODUCTION

Image fusion has received significant attention in remote sensing. It can be defined as the process of combining two or more source images from the same scene into a composite image with extend information content by using a certain algorithms. The fused image may provide increased interpretation capabilities and more reliable results since data with different characteristics. The process of image information fusion can be performed at signal, feature, and symbol levels depending on the representation format at which image information is processed. (Ranchin, 2003).

The objective of image fusion is to improve the accuracy of the objective recognition and classification, which can support the decision making. The existing research results show that by fusing the panchromatic and multi-spectral images to gain the high spatial resolution multi-spectral fusion remote sensing images can effectively improve the accuracy of image classification. Besides fusing different classification results from different single feature sources at decision level can also be an effective way to improve the classification results.

This paper proposes an image fusion algorithm of remote sensing images based on extensions of independent component analysis (ICA) and multi-classifier system. Firstly a novel method of fusing panchromatic and multi-spectral remote sensing images is developed by contourlet transform. Then using different features extracted from the extension of ICA domain coefficients of the fused images, a parallel and stack multi-feature and multi-classifier decision level image fusion algorithm is presented. The remainder of the paper is organized as follows. Section 2 recalls the concept of contourlet transform. Section 3 introduces the foundations and extensions of ICA.
Section 4 highlights the algorithm of the decision fusion algorithm based on extension of ICA and multi-feature and multi-classifier system. Experiments results and comparisons are presented and discussed in Section 5. Conclusions are drawn in Section 6.

2. CONTOURLET TRANSFORM

The contourlet transform (M.N.Do, 2002) is an extension of the wavelet transformation in two dimensions using multi-scale and directional filter banks. The contourlet expansion of images consists of basis images oriented at various directions in multiple scales, with flexible aspect ratios. Thus the contourlet transform not only retains the multi-scale and time-frequency localization properties of wavelets, but also it offers a high degree of directionality and anisotropy. The contoulet transform is implemented in two stages: the subband decomposition stage and the directional decomposition stage.

Recently developed contourlet transform can offer a much richer set of directions and shapes, and thus it is more effective than wavelet in capturing smooth contours and geometric structures in images. This paper proposes a novel method of fusing panchromatic and multi-spectral remote sensing images based on contourlet transform.

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3. EXTENSION OF ICA

3.1 Independent Component Analysis

Independent component analysis (ICA) (Hyvarinen,1999) is a newly developed linear data analysis method to separate blind sources, which has been used in some challenging fields of medical signals analysis, features extraction and pattern recognition. The ICA model is defined as:

$$x = A \bullet s \tag{1}$$

Where x is observed random vector, s is source random vector. The ICA solution for the unmixing problem is to find a linear transformation $\mathbf{W}$ of dependent sensor signals x, that makes the ouputs y as independent as possible, i.e.

$$y = W \bullet x \tag{2}$$

Where y is an estimate of sources.

The main task of ICA is to solve the separation matrix $\mathbf{W}$, the key of algorithms is to choose the method that measure the independence between signals. A large amount of algorithms have been developed for performing ICA. One of the best methods is the fixed point FastICA algorithm. In the FastICA algorithm, negentropy is used as the criterion to estimate y as it is a natural measure of the independent between random variables. The goal is to maximize their negentropy. In the FastICA algorithm, the negentropy is approximated by using the contrast function which has the following form:

$$Ng(y) = \{E[G(y)] - E[G(y_{gauss})]\}^2 \tag{3}$$

Where y is random vector, y_{gauss} is a standardized gaussian variable. $E[\cdot]$ is mathematics expectation, $G[\cdot]$ is a non-quadratic function. Here we choose:

$$G(u) = -\exp(\frac{-u^2}{2}) \tag{4}$$

3.2 Extension of Independent Component Analysis

3.2.1 Topographic Independent Component Analysis: As the estimated independent components by standard ICA are not completely independent, the residual dependence structure could be used to define a topographic order for the components. Topographic Independent Component Analysis (TICA) is a well-known ICA-based technique, which uses the topographic order representation to combines topographic mapping with ICA. In contrast to ICA, the components s are no longer independent but mutually energy-correlated according to the two-layer generative model (Hyvarinen,2001). TICA assumes that the variances of sources are dependent on each other through neighborhood functions. This idea leads to the following representation of the source signals:

$$s_i = \sigma_i z_i \tag{5}$$

Where z_i is a random variable having the same distribution as s_i, and the variance σ_i is fixed to unity. The variance σ_i is further modeled by nonlinearity:

$$\sigma_i = \phi(\sum_{k=1}^{n} h(i,k)u_k) \tag{6}$$

Where u_i are the higher order independent components used to generate the variances, $h(i,j)$ is a neighborhood function, and ϕ describes some nonlinear.

Then TICA is given as the following update equation:

$$w_{ij} := w_{ij} + \alpha E\{z(w_i^T z) r_i\} \tag{7}$$

where $E(u)$ is the expectation operator, α is the stepsize, and

$$r_i = \sum_k h(i,k) g(\sum_j h(k,j)(w_j^T z)^2) \tag{8}$$

The function g is the derivative of G, such as $\tanh$ etc.

3.2.2 Improved Neighborhood Kernel Function: The neighbourhood function $h(i,j)$ expresses the proximity between the i-th and j-th components. It can be defined in the same ways as with the self-organizing map. At the present time only the most common square type neighbourhood function are used in the standard TICA，i.e.

$$h(i,j)=\begin{cases}1, & if\ |i-j|\le m\\ 0, & otherwise\end{cases} \tag{9}$$

The constant m defines the width of the neighborhood.

In fact from the view of neurobiology the feedback intensity between the central cell and other neighbor cells has business with the distance，so neighborhood should be the function of distance. Considering the characteristics of human visual system and under our many experiments, this paper introduces the gaussian neighborhood series kernel function to express the different topology of TICA, such as:

$$h_g(w_{ij},w_{nm})=e^{-\frac{1}{2}[\frac{\sqrt{(i-n)^2+(j-m)^2}}{r}]^2} \tag{10}$$

The new introduced neighborhood functions can obtain the image basis with obviously enhanced directionality, which has advantages for the coming image analysis task.

3.2.3 Modified Learning Rule: To resolve the separation matrix **W**, the optimization problem can be induced as follows:

$$\textbf{\textit{min}}\ \ J(w)=\ E\{G(\sum_{i=1}^{n}h(i,j)(w_i^T z(t))^2)\}$$
$$\textbf{\textit{subject to}}\ \|w\|_2^2=1 \tag{11}$$

The Lagrange function can be derived as:

$$L(w,\lambda)=-E\{G(\sum_{i=1}^{n}h(i,j)(w_i^T z(t))^2)\}+\lambda(\|w\|_2^2-1) \tag{12}$$

Finally the batch learning rule can derived as:

$$w'=w-\eta(E\{g(y)z\}-E\{g(y)y\}w) \tag{13}$$

Where η is learning rate, here the self-adaptive adjustment method is developed in this paper.

Through introduction of Lagrange operator to solve the optimization of TICA, the method has religious deduction procedure and well property of convergence.

In short, this paper introduces the new topographic kernel functions to express the relationships between the independent components, which can better satisfy the human vision system demand than the former model. Further more, the paper also gives the new optimization rule to realize the farther development of TICA. The proposed modified TICA is more applicable in image fusion.

The information that remote sensing image represent is the reflectivity of different objects in certain band. Each band of multi-spectral remote sensing images can be considered as the combination of reflectivity of the several independent land objects in certain law. Applying ICA to multi-spectral remote sensing images, we can obtain the independent component bands that concentrate the information of specific land objects, resulting in enhancing the degree of separation of different objects.

For single band remote sensing image, most important information such as edge features, texture features are nearly correlative with high-order statistics. High-order statistics reflect the important structure and phase feature of image. Image analysis using ICA/TICA with high-order statistics has particular advantage, it can realize sparse coding, meanwhile, ICA/TICA is excellent edge filter (Zeng,2005). When people observe image, a series image patches are picked up firstly and then the whole image. Suppose each image patch is denoted by x, which can be regarded as a linear combination of the base function matrix **A**, independent component s is the statistic independent random vector, expressing the coefficients that the corresponding basis act on image, i.e. $x=\sum_{i=1}^{N}a_i s_i$, where $\mathbf{A}=(a_1,a_2,\cdots,a_N)$,column vector $a_i(i=1,2,\cdots,N)$ denotes a group of $N^2\times 1$ pixels basis images. Through ICA resolves the separation matrix **W**, one can get the coefficients projected in independent component basis by $y=\mathbf{W}x$, which express the image features in ICA domain. Figure.1 are basis matrix **A**, basis vectors have orientation in space domain and localization in frequency domain, depict most of the edge features of image. Figure.2 illustrates the basis vectors obtained by our improved TICA, one can observe the spatial correlation of basis introduced by topography, the basis offer a more comprehensive representation compared to the general ICA model.

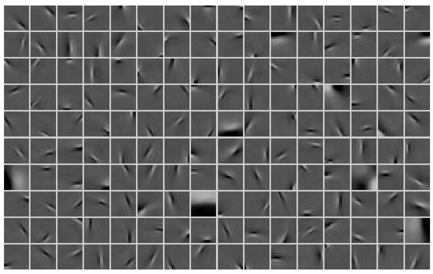

Figure 1. ICA basis of natural image data

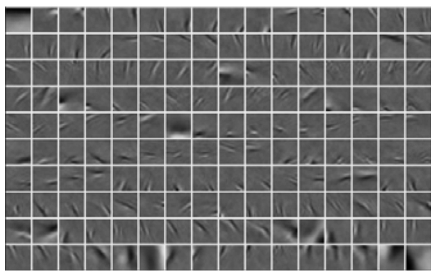

Figure 2. Improved TICA basis of natural image data

4. IMAGE FUSION ALGORITHM BASED ON EXTENSIONS OF ICA AND MULTI-CLASSIFIER SYSTEM

This part introduces the decision level remote sensing image fusion algorithm. Existing studies have show that by fusing multi-spectral images and panchromatic image to get the high quality fusion images can improve the accuracy of classification than just using single source image. This paper uses the panchromatic image, multi-spectral images and the resulting fused images for researching objects, extracting the spectral features, texture features and the features in ICA and TICA transformation domain, using different classifiers to get the classification results corresponding to different features and applying the method of multi-classifier system to obtain the final classification of land cover from remote sensing images.

4.1 Image Fusion Based on Contourlet Transform

Coregister both images and resample the multi-spectral images to make its pixel size equal to that of the panchromatic image in order to get perfectly superposable images. Here only R/G/B three channels are considered. The images are firstly decomposed by contourlet transform, getting low frequency and high frequency coefficients in different resolutions and different directions. Then combining $\tilde{a}$trous wavelet, the fusion procedure is choosing different rules on particular sets of contourlet coefficients that correspond to high and low frequency bands. The high-frequency coefficients of the panchromatic image substitute all the high-frequency coefficients in R/G/B three channels. The panchromatic image is decomposed by $\tilde{a}$trous wavelet , getting a group of wavelet plane coefficients, then adding these wavelet coefficients to the low-frequency contourlet coefficients, that is further extracts the detail information of panchromatic image for fusing application. Final fused images are obtained by using reversed contourlet transform.

The proposed method can get more information in the fused results and the spectral reserving character is quite well. The contourlet transform image fusion method offers a desirable result to improve spatial resolution and information of the fused images, which get ready for the next classification procedure.

4.2 Image Feature Extraction

4.2.1 Spectral Feature: The spectral features of multi-spectral images are the most essential features, here the three channels of high spatial resolution fused images are considered. Besides the spectral features extracted in the original R/G/B color space, other image features can be gotten by transforming the multi-spectral fused image into different color space. How to choose the suitable color space is an important factor for different color space can define different useful spectral features. So there are two key points should be considered in choosing color space, one is that the color space can present the irrelevant color features, the other is that the color space remains constant in different illumination conditions. Based on the above considerations, the paper chooses the Ohta color space(Ohta,1985) which can be expressed as following.

$$\begin{cases} I_1 = (R + G + B) / \mathbf{3} \\ I_2 = (R - B) / \mathbf{2} \\ I_3 = (\mathbf{2}G - R - B) / \mathbf{4} \end{cases} \tag{14}$$

The components in Ohta color space are irrelevant, so it can well apperceive the change of color in statistical view. Ohta color space is gotten by linear transform of RGB color space, here $\mathbf{I_1}$ is the intensity component, $\mathbf{I_2}$ and $\mathbf{I_3}$ are the almost orthogonal color components. The feature vectors obtained from Ohta color space are denoted by $\mathbf{T_1}$ here.

4.2.2 Texture Feature of TICA basis: Since the original panchromatic image has high spatial resolution and low spectral resolution, different objects have the same gray value or the same object has different gray values in the panchromatic image sometimes. As the fused images can have high spatial and spectral resolution simultaneously, the fused color images are transformed into the grayscale image named grayscale modulation image (GMI) here by specific algorithm. GMI is useful information source because its spatial resolution is similar to the original panchromatic image and its gray spectral values can reflect different objects much better. So by applying TICA to the GMI block by block in sliding window style, the texture features of TICA basis can be extracted.

In order to uncover the underlying structure of an image, it is common practice in image analysis to express an image as the synthesis of several other basis images. These bases are chosen according to serve some specific analysis tasks. The advantage of the TICA basis is that the estimated transform can be tailored to the needs of the application. A set of images with similar content to the GMI is selected for training the desired bases. Then using the TICA basis the GMI is transformed into the TICA domain in sliding $N \times N$ window style. All of these extracted TICA features can well reflect the structure and texture information of the fused images. The TICA feature vectors are denoted by $\mathbf{T_2}$ here.

4.2.3 Independent Component Feature: The existing studies show that the correlation between the bands of multi-spectral images sometimes brings ill effect in image classification. ICA not only can remove the correlation in the bands of multi-spectral images, but also can makes the resulting components mutual independent as much as possible. The every resulting band of independent component embodies a concentrated reflection of certain ground objects, increasing the degree of separation between different ground objects. Therefore independent component analysis can effectively remove the unfavorable influence and raise the accuracy of classification.

Multi-spectral images can be regarded as the linear combination of multi-source mixture signals in some sense due to their low spatial resolution. This paper treats the panchromatic and multi-spectral images as four dimensional mixture signals and adopts ICA to obtain another fusion scheme of multi-spectral and panchromatic images to get three dimensional multi-spectral images. Though the resulting independent components can not reserve the original spectral characteristics very well, they can express the sharpened multi-spectral images and resolve the problem of unmixing the mixed multi-spectral images pixels in the hypothesis of linear spectral mixture model, which lay the foundation for the next step of properly classification. The extracted three independent component features are recorded as **T3** here.

By means of the methods of feature extraction mentioned above, this paper can get three major feature of fused images, i.e. spectral feature (**T1**), texture feature of TICA (**T2**) and linear transform feature of ICA (**T3**).

4.3 Multi-Classifier Construction

4.3.1 Principle of Multi-Classifier System: Classification is the process of assigning presented information into classes and categories of the same type. The classification of the image requires the estimation of the posterior probability for each class. Such estimates can be obtained by using supervised and unsupervised classification algorithms.

The output of a classifier can take abstract form, rank level and measurement level. In the past few years, significant efforts have been devoted to the development of effective algorithms for combining different types of classifiers in order to exploit the complementary information that they provide(Burzzone,2001; Ranawana,2006). So if a multi-classifier system is to be successful, the different classification should have good individual performances and be sufficiently different from each other. A multi-classifier can be constructed either in a parallel, stack or combined manner. Once the individual classifiers have been designed and implemented, the next most important task involves the combination of the individual results obtained through each individual classifier. The strategy includes linear combination methods, non-linear combination methods, statistical methods and computationally intelligent method.

The success of a multi-classifier system depends on three key features: proper selection of classifier with diversity, topology and combinational methodology. The main purpose of multi-classifier combination is to take advantage of the different classifiers to enhance the generalization ability of the individual classifier to gain the better results of classification. This paper makes a useful attempt in the multi-classifier system and proposes a multi-classifier fusion method base on extension of ICA.

4.3.2 Classifier Selection: Corresponding to the three different features in the fused images, this paper makes the pointed choice the following classifiers, including K-NN classifier, BP neural network classifier, decision tree classifier and multi-category SVMs.

1. K-nearest neighbor classifier, K-NN. The K-NN has a very effective strategy as a learner, it keeps all training instances. A classification is made by measuring the distances from the test instance to all training instances, most commonly using the Euclidean distance. From these distances, a distance matrix is constructed between all possible pairings of points. The data points, k-closest neighbors are then found by analyzing the distance matrix. The k-closest data points are then analyzed to determine which class label is the most common among the set. Finally the majority class among the K nearest instances is assigned to the test instance. K-NN classifier is denoted by C1 here.

2. BP neural network classifier. Back-propagating network (BP network) is a type of neural network. When positive direction spread, the imported model disposes layer by layer by way of hidden units from the input layer and sent to the output layer, neural state of each layer only affects state of the next layer. If the expected output can not be obtained in the output layer, so transfer to back propagation, and let error signal back along the original link pathway, the error signal can became least through amend the values of each nerve cell. This paper chooses the BP neural network with one hidden layer and uses C2 denotes it.

3. Decision tree classifier. The decision tree classifier is a set of hierarchical rules which are successively applied to the input data. Those rules are thresholds used to binary split the data into two groups. Each node is such that the descendant nodes are purer in terms of classes. Decision tree rules are explicit and allow for identification of features which are relevant to distinguish specific classes. Then the analysis is reduced to the most useful layers. The structure of the decision tree can also be reveal hierarchical and nonlinear relationships among input layers. These relationships often result in a given class being described by various terminal nodes. Terminal nodes are the final decision, which assign a sample to certain class. Here decision tree classifier is denoted by C3.

4. Support vector machines, SVMs. Support vector machines (SVMs) is a kind of machine learning based on statistical learning theory(Vladmir,2000). The basic idea of applying SVMs to pattern classification can be stated briefly as follows: firstly map the input vectors into one feature space, either linearly or non-linearly, which is relevant with the selection of the kernel function. Then with the feature space from the first step construct a hyperplane which separates two classes,.This can be extended to multi-class.

The commonly used four kernel function in SVMs are: linear function, polynomial function, radial basis function, sigmoid function. SVMs have the important computational advantage that no nonconvex optimization is involved. Moreover, its performance is related to the margin with which it separates the data. As a new classification technique, SVMs outperforms many conventional approaches in various applications. Here SVMs classifier is denoted by **C4.**

4.3.3 Strategy of Multi-Classifier Fusion: Corresponding to the three different features extracted from the fused images and the four different selected classifiers, this paper constructs the parallel topology of multi-classifiers firstly, detail descriptions are as followings.

Towards the spectral features T1 in Ohta color space, K-NN C1 and decision tree C3 are chosen and combined in parallel topology. All the feature vectors are put into the two classifiers and respective classification results are obtained in parallel topology style.

For texture features of TICA basis, the paper chooses K-NN C1 and BP neural network classifier C2 and combines them in parallel style, resulting two respective classification results.
In regard to independent component features T3, K-NN C1 is chosen to get the corresponding classification results.

A number of training area for different classes are chosen in the study images, following the above methods to extract spectral and ICA/TICA image features, then training all the chosen classifiers and the trained classifiers are applying to classify the whole fused images every pixel. Through different classifiers the corresponding posterior probability of different classification results are gotten, so decision level fusion of these classification results is needed.

4.3.4 Decision Fusion Strategy: There are many strategies for combining classification results of each individual classifier, of which majority voting principle and Bayesian combination strategy are the most common used fusion method.

1.Majority Voting Principle: The majority voting method selects the relevant class by polling all the classifiers to see which class is the most popular. Whichever class gets the highest vote is selected. This method is particularly successful when the classifiers involved output binary votes.

2.Bayesian Combination Strategy: Bayesian combiners are used to carried out the classification according to the Bayes rule by selecting the class associated with the maximum average probability.

3.The proposed Fusion Strategy: Different from the routine fusion strategy, this paper adopts SVMs C4 to fuse the different classification results corresponding to different image features to get the final fusion decision. Each classification results of respective classifiers serve as the input feature vectors for training SVMs, which can be regarded as stack multi-classifier fusion style and the continuation of the aforementioned parallel multi-classifier system. The total fusion topology is as figure 3. Moreover the above common fusion rules are also used to get the classification results corresponding to different features.

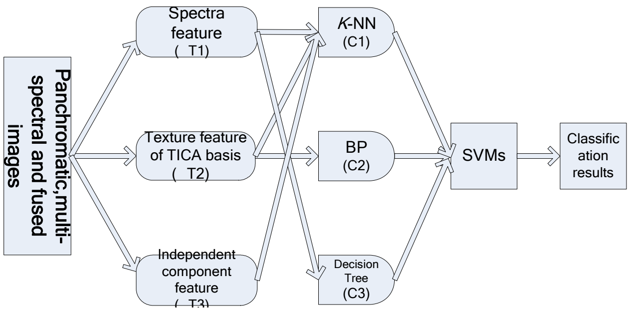

Figure 3. paradigm of multi-feature and multi-classifier fusion

5. EXPERIMENTAL RESULTS

In this paper, to illustrate the proposed fusion procedure with an example, the data used for this experiment are SPOT panchromatic and Landsat TM 5/4/3 multi-spectral images, with the same size of 256×256 pixels. Figure. 4(a) ~ 4(b) are the panchromatic image and the corresponding multi-spectral images. The experimental area can be classified into water body (including river, paddy field), naked land (including road, residential area, bridge and other undeveloped filed) and dry land by human visual interpretation. The fused images using contourlet transform to fuse SPOT panchromatic and TM multi-spectral images are shown in Figure.4(c).

The training area of water body, naked land and dry land are selected in the images, every category has two block of 16×16 pixels training samples, theses samples of three component values in Ohta color space correspond to the first type of input feature vectors, i.e. T1.

The fused color images are transformed into the GMI. Then applying TICA to the GMI with 2×2 pixels of block in sliding window style to get four coefficients of TICA domain, meanwhile, the statistical parameters, such as mean, standard deviation, average gradient are computed for the second type of input feature vectors, i.e. T2.

Turning the original multi-spectral images into 3×65536 pixels vectors and converting the original panchromatic image into 1×65536 pixels vector to form 4×65536 pixels input vectors, applying ICA to the whole input vectors, three independent component bands are shown in Figure.5 (a)~ (c). The results indicate that the three independent components play good role in separate the water body, naked land and dry land. Meanwhile the resulting fused false color images in Figure.5(d) have higher spatial resolution compare to the original multi-spectral images. All these three independent components are chosen as feature vectors for classification, i.e. T3.

The training areas for different classes are chosen in the images, following the above methods to extract spectral and ICA/TICA image features and training all the chosen classifiers, the trained classifiers are then applying to classify the whole fused images every pixel. Selecting suitable SVMs kernel function and parameter to train multi-category SVMs with the input feature vectors of every category obtaining from the afore parallel classifiers. The trained multi-category SVMs are applying to classify the whole fused images to gain the classification results. This paper chooses the radial basis kernel function:

$$K(x, x') = \exp(\|x - x'\|^2 / 2\sigma^2), \text{ where } \sigma = 2, \ C = 100。$$

The classification results corresponding to different fusion rules are shown as follows. To test the effect of the proposed algorithm, the common fusion rules and the proposed novel multi-feature and multi-classifier algorithm for classification are showed in Figure.6 (c) and (e). Besides, the traditional min-distance method and the max-likelihood method of remote sensing image classification results are showed in Figure. 6(a) and (b).To evaluate the classification results objectively, the total classification accuracy is employed to describe the classification precision of the images by computing the degree of confusion between the statistical samples and the actual samples through sampling randomly in classification results. Table 1 is the comparison of total classification accuracy according to different classification methods.

Figure.4 Original SPOT(a), TM5/4/3 images(b) and fused images by contourle transform(c)

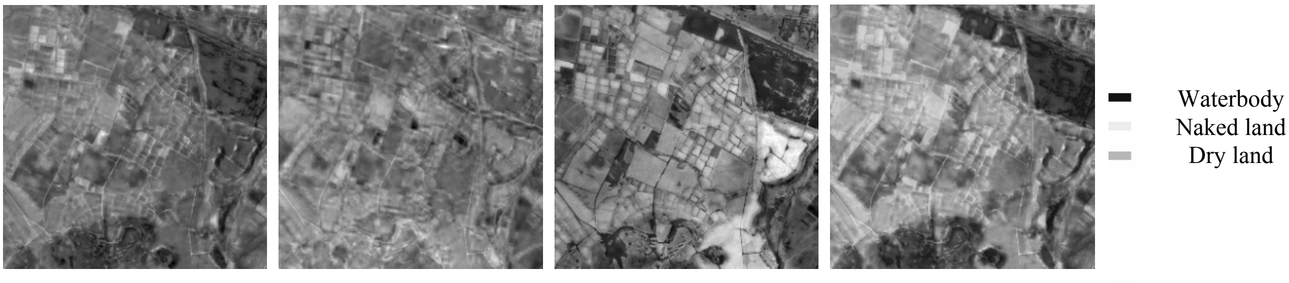

Figure.5 The three independent component bands(a,b,c) of the fused image by ICA(d)

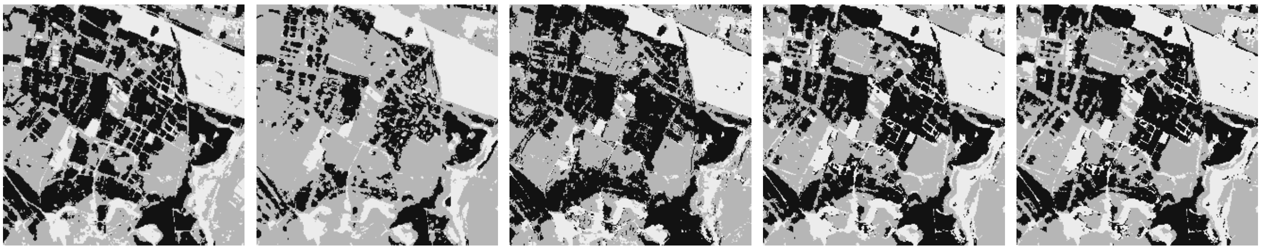

Figure. 6 classification results using different methods((a)Min Distance(b)Max Likelihood(c)Majority Voting(d)Bayesian Combination(e)Proposed Algorighm)

Classification algorithm	Total accuracy（%）
Min Distance	62.58
Max Likelihood	65.44
Majority Voting Principle	78.53
Bayesian Combination Strategy	81.80
Proposed Algorithm	82.21

Table 1 the comparison of total accuracy of classification using different methods

6. CONCLUSION

Remote sensing image classification is an important means for quantified remote sensing image analysis, and remote sensing image fusion can effectively improve the accuracy of image classification. This paper proposes an image fusion algorithm based on extension of ICA and multi-classifier system. A novel method of fusing panchromatic and multi-spectral remote sensing images is developed by contourlet transform that can offer a much richer set of directions and shapes than wavelet. As ICA not only can effectively remove the correlation of multi-spectral images, but also can realize sparse coding of images and capture the essential edge structures and textures of images, then using features extracted from the extensions of ICA domain coefficients of the images, different classifiers corresponding to different features are chosen in parallel multi-classifier style and the SVMs as stack fusion style are trained to classify the whole images in the proposed multi-feature and multi-classifier system. Experimental results show that the proposed algorithm can effectively improve the accuracy of image classification.

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