Advanced processing techniques for remotely sensed imagery

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Abstract: This paper reviews the recently developed processing techniques for remotely sensed imagery, including very high resolution (VHR) information extraction, super resolution techniques, hyperspectral image processing and object detection, and also some artificial intelligence approaches.

Key words: high resolution, super resolution, hyperspectral, artificial intelligence

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Recently, remotely sensed images with very high resolution (such as QuickBird, IKONOS, SPOT5, etc.) and hyperspectral channels (Hyperion, MODIS, MERIS, etc.) have been able to provide a large amount of information, thus opening up avenues for new remote sensing applications (e.g., urban mapping, environmental monitoring, precision agriculture, human—environment—earth interaction, etc.). However, their availability poses challenges to image processing and classification techniques due to the rich spatial and spectral information in the high resolution data and the hyper-dimensional features. It is agreed that conventional approaches are grossly inadequate for these new sensors. In this context, this paper aims to review the recent developments in image processing techniques for these new types of data. The paper is organized as follows. The first section discusses the information extraction and classification of the high spatial resolution images, including spatial feature extraction and object-based analysis. The second part concerns the super resolution reconstruction techniques. Section 3 describes the hyperspectral data analysis and Section 4 discusses the artificial intelligence approaches for remote sensing applications.

1 ADVANCED PROCESSING OF HIGH SPATIAL RESOLUTION IMAGERY

Commercially available very high resolution (VHR) satellite imagery (e.g., IKONOS, Quickbird, and SPOT-5) provides a large amount of spatial information. However, their availability poses challenges to image processing and classification techniques. The resulting high intra-class and low inter-class variabilities lead to a reduction in the statistical separability of the different land cover classes in the spectral domain, and conventional spectral classification methods have proven inadequate to interpret the VHR data (Myint et al., 2004; Zhang et al., 2006). It is well known that the combination of spatial and spectral information can effectively address this problem. The recent developments for spectral-spatial classification can be divided into 1) spatial feature extraction, and 2) object-based analysis.

1.1 Spatial feature extraction

1.1.1 Wavelet transform features

Some researchers have used the wavelet transform to extract the spatial information in different orientations and frequencies. Myint et al. (2004) compared the wavelet features with the fractal, spatial autocorrelation, and the spatial co-occurrence approaches, and the results suggested that a multi-band and multi-level wavelet approach can be used to drastically increase the classification accuracy. The fractal techniques did not provide satisfactory classification accuracy. Spatial autocorrelation and spatial co-occurrence techniques were found to be relatively effective when compared to the fractal approach. The experiments concluded that the wavelet transform approach was the most accurate of all four approaches. Zhang et al. (2006) extracted the spectral-textural information by decomposing the image into four sub-bands at different frequencies and resolutions and then integrating the low and high frequency information as spectral-textural features. Their experiments on QuickBird datasets verified that the utility of wavelet features can extract the spatial information effectively and help improve the pure spectral classification for high resolution images. Meher et al. (2007) utilized the extracted features obtained by the wavelet transform (WT) rather than the original multispectral features of remote sensing images for land cover classification. WT provides the spatial and spectral characteristics of a pixel.
along with its neighbors, and hence this can be utilized for an improved classification. The performance of the original and wavelet-feature (WF)-based methods were compared in experiments. The WF-based methods consistently yielded better results, and the biorhogonal3.3 (Bior3.3) wavelet was found to be superior to other wavelets.

1.1.2 Gray level co-occurrence matrix (GLCM)

Puissant et al. (2005) examined the potential of the spectral/textural approach to improve the classification accuracy of intra-urban land cover types. The second-order statistics of the gray level co-occurrence matrix were used as additional bands. In experiments, four texture indices with six window sizes created from panchromatic images were tested on images at high to very high resolutions. The results showed that the optimal index improving the global classification accuracy was the homogeneity measure, with a 7 by 7 window size. Ouma et al. (2008) presented the results of GLCM texture analysis for the differentiation of forest and non-forest vegetation types in QuickBird imagery. The optimal GLCM windows for land cover classes within the scene were determined using semi-variogram fitting. These optimal window sizes were then applied to eight GLCM texture measures (mean, variance, homogeneity, dissimilarity, contrast, entropy, angular second moment, and correlation) for the scene classification. The experimental results were the following: (1) the spectral-only bands classification gave an overall accuracy of 58.69%; (2) the statistically derived 21 by 21 optimal mean texture combined with spectral information gave the best results among the GLCM optimal windows with an accuracy of 73.70%.

A key issue for the window-based image processing techniques (e.g., GLCM texture) is the adaptive window selection approach. Although it is well known that combining spectral and spatial information can improve land use classification of very high resolution data, many spatial measures refer to the window size problem, and the success of the classification procedure using spatial features depends largely on the window size that was selected. Huang et al. (2007a) proposed an optimal window selection method based on the spectral and edge information in a local region for choosing the suitable window size adaptively, and the multiscale information was then fused, based on the selected optimal window size. The spatial features that were extracted by the gray-level co-occurrence matrix (GLCM) were utilized for multispectral IKONOS data, in order to validate the window selection algorithm. The results showed that the proposed algorithm could select and fuse the multiscale features effectively and, at the same time, increase the classification accuracy.

1.1.3 Structural and shape features

Benediktsson et al. (2003) used a composition of geodesic opening and closing operations of different sizes in order to build a morphological profile and a neural network approach for the classification of features. The experiments were conducted on panchromatic images of IKONOS with 1m spatial resolution, and the results showed that the morphological features can create adequate spatial information and significantly improve the accuracies of the traditional classifiers. The morphological features were extended for use with airborne images in Benediktsson et al. (2005) and a joint spectral/spatial classifier was presented. The morphological method was based on making use of both the spectral and spatial information for classification and principal component analysis (PCA) was employed for pre-processing and dimensionality reduction. Epifanio and Soille (2007) exploited the morphological texture features to segment high resolution images of natural landscape into several cover types. The texture features were of interest because the number of available spectral bands in high resolution images is sometimes limited; in addition, the traditional pixel-based classification techniques perform poorly. Huang et al. (2007b) investigated the classification and extraction of spatial features in urban areas from high spatial resolution multispectral imagery. A structural feature set (SFS) was proposed to extract the statistical features of the direction-lines histogram. Some methods of dimension reduction, including decision boundary feature extraction and the similarity index feature selection, were then implemented for the proposed SFS to reduce information redundancy. The approach was evaluated on two QuickBird datasets and the results showed that the new set of reduced spatial features had better performance than traditional methods.

1.2 Object-based analysis

1.2.1 Development of the object-based algorithms

Object-based classification is a good alternative to the traditional pixel-based methods. This analysis approach will reduce the local spectral variance within a homogeneous region. The basic idea of this method is to group the spatially adjacent pixels into spectrally homogeneous segments, and then perform classification on objects as the minimum processing units. Ketig and Landgrebe (1976) firstly proposed the object-based analysis approach and developed the spectral-spatial classifier called the extraction and classification of homogeneous objects (ECHO) (Landgrebe, 1980). Jimenez et al. (2005) developed the unsupervised version of the ECHO algorithm, namely UnECHO, which was a method of unsupervised enhancement of pixel homogeneity in a local neighborhood. It enabled a contextual classification of multispectral or hyperspectral data, producing results that were more meaningful to the human analyst. Their experiments on HYDICE and AVIRIS showed that the UnECHO classifier was especially relevant for the new generation of airborne and spaceborne sensors with high spatial resolution.

In recent years, the fractal net evolution approach (Hay et al., 2003), which is embedded in the eCognition commercial software, has been widely used for object-based analysis and experiments. It utilizes fuzzy set theory to extract the objects of interest, at the scale of interest, segmenting images simultaneously at both fine and coarse scales. The FNEA is a bottom-up region merging technique starting from a single pixel. In an
iterative way, at each subsequent step, image objects are merged into bigger ones. The region merging decision is made with local homogeneity criteria and the criteria are defined as:

\[
H = \sum_{b=1}^{B} W_b^b [ N_{\text{Merge}} \sigma_{\text{Merge}} - (N_{\text{Obj}1} \sigma_{\text{Obj}1} + N_{\text{Obj}2} \sigma_{\text{Obj}2}) ]
\]  

(1)

where \(W_b^b\) is the weight for band \(b\), \(N_{\text{Merge}}, N_{\text{Obj}1}, \) and \(N_{\text{Obj}2}\) represent the number of pixels within the merged object, object 1, and object 2, respectively. \(\sigma_{\text{Merge}}, \sigma_{\text{Obj}1}, \) and \(\sigma_{\text{Obj}2}\) are respective standard deviations. When a possible merge of a pair of image objects is examined, the fusion heterogeneity value \(H\) between those two objects is calculated and compared to the scale parameter \(T\). The two objects are merged when \(H < T\). The scale parameter is a measure of the maximum change in heterogeneity that may occur when merging two image objects.

Watershed transformation in mathematical morphology is a powerful tool for image segmentation and can also be employed for object-based analysis. Li and Xiao (2007) presented an extension of the watershed algorithm for image segmentation. A vector-based morphological approach was proposed to calculate gradient magnitude, which was then input to watershed transformation for image segmentation. The method showed encouraging results and can be used for segmentation of high resolution multispectral imagery and object based classification.

Akcay and Aksoy (2008) presented novel methods for automatic object detection in high resolution images by combining spectral information with structural information extracted using image segmentation. The segmentation algorithm was carried out using morphological operations applied to individual spectral bands with structuring elements of increasing sizes. The experimental results showed that the proposed methods were able to automatically detect, group, and label segments belonging to the same object classes.

1.2.2 The improved algorithms for object-based analysis

With increasing developments for object-based classification, some optimized algorithms have been proposed. Wang et al. (2004a) proposed a hybrid classification that integrates the pixel and object-based classifications. The pixel and object level maps were obtained using the maximum likelihood classifier and the nearest neighbor classification, respectively (namely, MLCNN). Gamba et al. (2007) proposed a boundary-optimized approach for high resolution image classification. The boundary and non-boundary pixels were discriminated and then classified separately. Bruzzone and Carlin (2006) developed a multilevel approach for high spatial resolution image processing. Its basic idea is the simultaneous use of multiscale representations as a feature extraction module that adaptively models the spatial context of each pixel. In experiments, its effectiveness was verified using urban and rural QuickBird images.

1.2.3 Applications for object-based analysis

Yu et al. (2006) exploited the multiple features from the object-based analysis approach to create a comprehensive vegetation inventory at Point Reyes National Seashore in Northern California. In their studies, for each object, 52 features were calculated including spectral features, textures, topographic features, and geometric features. Wang et al. (2007a, 2007b) investigated the object-based analysis for mangrove mapping at Punta Galeta on the Caribbean coast of Panama. Waske and van der Linden (2008) exploited the joint classification of multiple segmentation levels to fuse synthetic aperture radar (SAR) and optical remotely sensed data.

2 SUPER RESOLUTION (SR) RECONSTRUCTION TECHNIQUES

High resolution (HR) images are useful in many applications such as remote sensing, video frame freezing, medical diagnostics, and military information gathering, etc. However, because of the high cost and physical limitations of the high precision optics and image sensors, it is not easy to obtain the desired HR images in many cases. Therefore, super resolution (SR) image reconstruction techniques, which can reconstruct one or a set of HR images from a sequence of low resolution (LR) images of the same scene, have been widely researched in the last two decades.

The multi-frame SR problem was first formulated by Tsai and Huang (1984) in the frequency domain. They proposed a formulation for the reconstruction of a HR image from a set of under-sampled, aliased but noise-free LR images. Kim et al. (1990) extended the formulation to consider observation noise as well as the effects of spatial blurring. They solved the extended formulation by a weighted recursive least squares method to improve computational efficiency. Then Kim and Su (1993) extended their work by considering different blurs for each LR image. Rhee and Kang (1999) proposed a DCT-based algorithm in order to reduce computational costs. Furthermore, there have appeared a couple of papers that concentrate on wavelet SR methods (Chan et al., 2003; Lertrattanapanich & Bose, 2002; Ng et al., 2004). The advantage of the frequency domain methods is their low computational complexity; however, these methods are applicable only to global motion and a priori information about the high resolution image cannot be exploited.

Most of other super resolution techniques that have appeared in the literature operate in the spatial domain. Ur and Gross (1992) suggested a non-uniform interpolation method based on the generalized multi-channel sampling theorem of Papoulis (1977) and Yen (1956). The interpolation is followed by a de-blurring process and the relative shifts are assumed to be known precisely. Komatsu et al. (1993) presented a scheme to acquire an improved resolution image by applying the Landweber algorithm (Landweber, 1951) from multiple images taken simultaneously with multiple cameras. They employed the block matching technique to measure relative shifts. Alam et al. (2000) developed a technique for real-time infrared image registration and SR reconstruction. They utilized a gradi-
ent-based registration algorithm for estimating the shifts between the acquired frames and presented a weighted nearest neighbor interpolation approach. The advantage of the non-uniform interpolation approach is that it requires a relatively low computational load and makes real-time applications possible. However, in this approach, degradation models are limited (they are only applicable when the blur and the noise characteristics are the same for all LR images). Additionally, the optimality of the whole reconstruction algorithm is not guaranteed, since the restoration step ignores the errors that occur in the interpolation stage.

Irani and Peleg (1991) proposed an iterative back-projection (IBP) method adapted from computer-aided topography (CAT). In this method, the estimate of the high resolution image is updated by back-projecting the error between motion-compensated, blurred and sub-sampled versions of the current estimate of the high resolution image and the observed low resolution images, using an appropriate back-projection operator. The advantage of IBP is that it is understood intuitively and easily. However, this method has no unique solution due to the ill-posed nature of the inverse problem, and it has some difficulty in choosing the back-projection operator. In addition, it is difficult to apply a priori constraints.

Stark and Oskoui (1989) proposed a noteworthy POCS-based formulation to super resolution image reconstruction problems. In this method, the space of a high resolution image is intersected with a set of convex constraint sets presenting desirable image characteristics, such as positivity bounded energy, fidelity to data, smoothness, etc. Their approach was extended by Tekalp et al. (1992) to include observation noise and motion blur (Patti, 1994). Patti et al. (1997) extended the POCS approach to account for arbitrary sampling lattices and non-zero aperture time. The advantage of POCS is that it utilizes the powerful spatial domain observation model. It also allows a convenient inclusion of a priori information. These methods have the disadvantages of non-uniqueness of solution, slow convergence, and a high computational cost.

Another class of super resolution algorithms is based on stochastic techniques, including Maximum Likelihood (ML) (Tom & Katsaggelos, 1994) and Maximum A Posteriori (MAP) approaches (Guan & Ward, 1992; Schultz & Stevenson, 1994; Schultz & Stevenson, 1995; Schultz & Stevenson, 1996; Hardie et al., 1997). MAP estimation with an edge preserving Huber-Markov random field image prior is studied in Schultz and Stevenson (1994, 1995, 1996). MAP-based super resolution with simultaneous estimation of registration parameters (motion between frames) has been proposed in Hardie et al. (1997). Robustness and flexibility in modeling noise characteristics and a priori knowledge about the solution are the major advantages of the stochastic SR approach. Assuming that the noise process is white Gaussian, a MAP estimation with convex energy functions in the priors ensures the uniqueness of the solution. Therefore, efficient gradient descent methods can be used to estimate the HR image. It is also possible to estimate the motion information and the HR image simultaneously.

The precise registration of the sub-pixel motion is very important to the reconstruction of the HR image. However, precise knowledge of these parameters is not always assured in real applications. Lee and Kang (2003) proposed a regularized adaptive HR reconstruction considering inaccurate sub-pixel registration. Two methods for the estimation of the regularization parameter for each LR frame were advanced, based on the approximation that the registration error noise is modeled as Gaussian with a standard deviation proportional to the degree of the registration error. However, the convergence of these methods was not rigorously proved.

Robust super resolution techniques have appeared in Zomet et al. (2001), Farsiu et al. (2003), Farsiu et al. (2004), and take into account the existence of outliers (data that do not fit the model very well). In Zomet et al. (2001), a median filter was used in the iterative procedure to obtain the HR image. The robustness of this method is good when the errors from outliers are symmetrically distributed after a biased detection procedure. However, a threshold is needed to decide whether the bias is due to outlier or aliasing information. Also, the mathematical justification of this method was not analyzed. In Farsiu et al. (2003, 2004), a robust SR method was proposed based on the use of the $L_1$ norm in both the regularization and the measurement term of the penalty function. Robust regularization based on a bilateral prior is proposed to deal with different data and noise models. However, the pure translational assumption of the entire low resolution image sequence may not be suitable for some real data sequences.

There are several examples of the SR technique being successfully applied in the remote sensing area. The first multi-frame SR idea was motivated by the requirement to improve the resolution of Landsat remote sensing images. In 2002, CENS (National Space Study Center) successfully launched the SPOT5 satellite. Using the SR technique, SPOT5 can deliver a 2.5 meter panchromatic image through the processing of two 5 meter images, which are shifted to half a sampling interval by a double CCD linear array. Shen et al. (2007) proposed a SR reconstruction algorithm applied to real MODIS (moderate resolution imaging spectro-radiometer) remote sensing images in the same spectral band. They employed a truncated quadratic cost function to exclude the outliers in the sub-pixel registration part to obtain accurate photometric and geometric parameters among the observed images, and then used the MAP estimation with robust $L_1$ norm data fidelity and edge-preserving Huber prior to produce the desired HR image in the reconstruction part.

3 HYPERSONTICAL DATA PROCESSING

Recently, hyperspectral imagery has been attracting increased attention due to the wealth of information that can be extracted from these images for a variety of applications. Many military and civilian applications involve such areas as global
environment monitoring, mapping, geology, forestry, agriculture, and water quality management, and so on. These images are capable of producing a large amount of data very quickly due to the high resolution sampling of both the spatial and spectral dimensions. The processing cost for the large quantity of data may be very large. A great deal of research has aimed to find more efficient ways to process this data type, and recent research methodologies can be classified into two kinds: pure and mixed pixel methods.

3.1 Pure pixel based methods

These methods are based on the hypothesis that all the pixels in the images are composed of one kind of land object. Pure pixel based methods can be separated into two sub-groups: vegetation index and statistical methods.

3.1.1 Vegetation Index methods

Vegetation Index is the parameter extracted from the spectral features of objects, including spectral matching recognition and land object reconstruction (Goetz, 1997). In these methods, the spectral spots measured by fieldwork are compared with those extracted by the imaging spectrometers to distinguish different classes. In order to improve the efficiency and speed of the analysis of hyperspectral data from the imaging spectrometers, these spectral spots are usually coded to extract their spectral features. Kruse et al. (1993) proposed spectral matching, which is one of the most widely used methods for analyzing hyperspectral data. The main problem of the Vegetation Index is that it is difficult to construct a universal Vegetation Index to be suitable for most of the hyperspectral data. Zhang et al. (2006, 2007) developed a universal pattern decomposition method (UPDM) to construct a VIUPD.

3.1.2 Statistical methods

Statistical methods are very important in hyperspectral data processing and are especially widely used in target detection and classification of hyperspectral data. In these methods, each band is regarded as a random variable, and the probability statistics methods are then applied to extract statistical characters of the image. Due to the hyper-dimensionality, dimension reduction has to be done first to reduce the computational time. The most important application of statistical methods is anomaly detection. The hyperspectral data are considered to have a certain distribution and the anomalies are the pixels that do not fit the distribution. RX and its extended algorithms (Yu & Reed, 1993; Kwon & Nasrabadi, 2005; Hruschka & Ebecken, 1999) are efficient methods for anomaly detection.

3.2 Mixed pixel based methods

Due to the complex conditions in the field and the limitation of spatial resolution of the hyperspectral data, mixed pixels occur widely in hyperspectral data (Zhang & Li, 1998). Mixed Pixel Models were proposed to solve the above problem. The models are summarized as two types: linear mixture models and non-linear mixture models. The linear mixture model is most widely used as it is very simple and usually has clear physical meaning. However, by the use of a linear mixture model, the number of classes to be extracted should be smaller than the number of bands of the hyperspectral data. In order to avoid the limitation of linear mixture models, non-linear models were proposed and the mixed pixels were expressed as the sum of residual error and the high order moment of the endmembers.

One of the most important applications of mixed pixel based methods is to detect sub-pixel targets in hyperspectral data. Recently, sub-pixel target detection methods have mainly focused on the linear mixture model and matched filter to find the possible occurrence of a target spectrum in the pixels of the hyperspectral data. OSP (Orthogonal Subspace Pursuit) (Chang, 2005), PP (Projection Pursuit) (Chiang et al., 2001) and CEM (Constrained Energy Method) (Settle, 2002) are the widely used methods. Recently, several new algorithms were introduced into sub-pixel target detection, such as kernel-based methods (Nasrabadi & Kwon, 2005; Kwon & Nasrabadi, 2004; Gu et al., 2008; Kwon & Nasrabadi, 2006) and morphology-based methods (Roberts et al., 1998). In addition, another factor affecting the detection results is the spectral variability. Several models were proposed to solve the problem, such as the sub-space approach (Kwon & Nasrabadi, 2006).

The other important applications of mixed pixel based methods are endmember extraction and the mixture pixels decomposition. The endmember extraction can be performed in two ways: (1) by deriving them directly from the image (image endmembers), or (2) from field or laboratory spectra of known target materials (library endmembers); see Roberts et al. (1998) for a comparison of the two. The risk in using library endmembers is that these spectra are rarely acquired under the same conditions as the airborne data. Image endmembers have the advantage of being collected at the same scale as the data and can thus be more easily associated with features in the scene. An image endmember (IE) is obtained by locating a pixel in the scene with the maximum abundance of the physical endmember it will represent, but there may be cases where it is not possible for a certain algorithm to find such pure pixels in a scene. During the last decade, several algorithms have been proposed for the purpose of autonomous/supervised endmember selection from hyperspectral scenes, including the manual endmember selection tool (MEST) (Bateson & Curtiss, 1996), pixel purity index (PPI) (Bowles et al., 1995), N-FINDR, vertex component analysis (VCA) (Nascimento & Dias, 2005), iterative error analysis (IEA) (Neville et al., 1999), iterated constrained endmember(ICE) algorithm (Berman et al., 2004), optical real-time adaptive spectral identification system (ORASIS) (Boardman et al., 1995), and automated morphological endmember extraction (AMEE) (Plaza et al., 2004).

PPI, N-FINDR, CCA, and VCA might be characterized as instances of the classic approach to endmember selection, based on the search for spectral convexities. While PPI is partially automated, N-FINDR, CCA, and VCA are fully automated. IEA
is based on an iterative process in which those pixels that reduce the error obtained in constrained spectral unmixing operations are used as endmembers. The ICE algorithm performs a least squares minimization of the residual sum of squares (RSS) based on the convex geometry model. On the other hand, ORASIS performs endmember selection by using LVQ concepts. Contrary to the methods above, which rely on spectral properties of the data alone, AMEE uses a morphological approach where spatial and spectral information are equally employed to derive endmembers.

In addition to the linear mixing models, which are often used in mixture pixels decomposition, several other non-linear unmixing models have been implemented in the past decade, including neural network, regression and decision trees, and kernel least squares analysis. The non-linear models, especially neural network based models, outperformed the traditional linear unmixing models. Multilayer Perceptron (MLP) is one of the most widely used neural network models for non-linear unmixing. Atkinson et al. (1997) applied a MLP model to decompose AVHRR imagery. It was superior to the linear unmixing model. Another popular neural network model, ARTMAP, was first introduced to identify the life-form components of the vegetation mixture (Carpenter et al., 1996). Landsat TM imagery was used to estimate sub-pixel information for life-form components. The ARTMAP-based mixture model was able to capture non-linear effects and thus performed better than the conventional linear unmixing models. Liu et al., (2006) applied a similar ARTMAP model for sub-pixel classification of MODIS imagery with the fused information of two sensors having different resolutions.

4 COMPUTATIONAL INTELLIGENCE TECHNIQUES FOR REMOTE SENSING IMAGE CLASSIFICATION

With the trends to high spatial resolution, high spectral resolution, high temporal resolution, multi-sensor, multi-flat, and multi-angle, earth observation technology by remote sensing is providing more and more remote sensing data for the research of earth resource environments. However, traditional processing technology is finding it difficult to adapt to the demands of current remote sensing information processing, because it requires prior assumptions or has a low processing precision and intelligence. Thus, up to now, the huge and valuable remote sensing data sets have not been used fully and effectively. Intelligent remote sensing image processing technology is an effective solution to the above problem because it does not need the prior assumptions and can automatically extract the image information. Hence, the research of intelligent remote sensing image processing technology has been a hot research topic in the field of remote sensing. Neural Networks (NNs) and Genetic Algorithms (GAs) are the main components of computational intelligence (CI) (Stathakis & Vasilakos, 2006). In addition, Artificial Immune Systems (AIS) inspired by the immune systems are recognized as a novel branch of computational intelligence. Each of these components has been individually applied to perform the task of remote sensing image classification.

4.1 Artificial Neural Networks (NNs)

Neural Networks are modeled after the constructs of the human brain, wherein intelligence is stored in neural pathways as well as in memory. In an artificial neural network, knowledge is stored in the form of weights applied to a node; that is, as multiplicative values to be applied to an input (Miller et al., 1995). Instead of algorithms to determine values, a supervised network is presented with repeated examples of inputs and corresponding correct outputs, and allowed to “learn” for itself. Human beings learn by experience; neural nets by setting weights that will produce a specified output. When the net finally is presented with new data, it applies the weights and the resulting output is consistent with previous experience (Miller et al., 1995).

A number of NN applications are available in the remote sensing (RS) literature. NNs are often reported to yield comparable or superior accuracy levels compared to statistical classifiers (Bischof et al., 1992; Bischof & Leonardis, 1998). They have also proven to be a suitable paradigm for multisource classification by the incorporation of ancillary information, such as topographic and contextual information, etc. (Benediktsson et al., 1990).

4.2 Genetic algorithm (GA)

Genetic algorithms (GAs) (Goldberg, 1989; Davis, 1991), inspired by natural evolution, are able to perform a randomized global search in a solution space by the principles of evolution and natural genetics. They are efficient, adaptive, and robust search processes, producing near-optimal solutions and have a large amount of implicit parallelism. GAs deal with individuals called chromosomes (usually binary strings), which encode the parameters of the problem space and represent potential solutions. An objective function of a string provides a mapping from the chromosomal space to the solution space. A fitness function is also associated with each string, which indicates the degree of ‘goodness’ of the solution represented by it. A set of chromosomes constitutes a population, which is initially created randomly. Biologically inspired operators like selection, crossover, and mutation are applied on the population over a number of generations until a termination criterion is achieved. The best string obtained at this point (or obtained so far) represents the solution of the problem (Pal et al., 2001).

In pattern recognition there are many tasks involved in the process of analyzing/identifying a pattern that need appropriate parameter selection and efficient search in complex spaces in order to obtain optimum solutions. Therefore, the application of GAs for solving certain problems of pattern recognition (which need optimization of computation requirements, and robust, fast
and close approximate solutions) appears to be appropriate and natural (Gelsema, 1995; Pal & Wang, 1996). They have also been used for parameter estimation in characterizing contextual information (Tso & Mather, 1999).

4.3 Artificial immune systems (AIS)

Artificial immune systems (AIS), inspired by the immune systems, are known as a novel branch of computational intelligence. They use the immunological properties in order to develop adaptive systems to accomplish a wide range of tasks in various areas of research (Dasgupta, 1999; de Castro & Timmis, 2002), including pattern recognition, intrusion detection, clustering, optimization, and intelligence control. As a new method in computational intelligence, AIS have a great application potential in intelligent processing of remote sensing images. Based on these situations, some researchers are studying the theory, models, and methods of the current AIS to propose new immune models and algorithms and to establish the theory for AIS and their applications to remote sensing image processing problems, such as unsupervised classification, unsupervised classification, and feature selection.

4.3.1 Unsupervised artificial immune classifier

A novel unsupervised machine-learning algorithm based on nature immune systems, namely the unsupervised artificial immune classifier (UAIC), is proposed to perform remote sensing image unsupervised classification (Zhong et al., 2006). In addition to their nonlinear classification properties, UAIC possesses biological properties such as immune recognition and immune memory. Therefore, UAIC is capable of performing data clustering by generating a representative set of memory cells for classification. To simulate the antibodies in immune systems, the antibody population (AB) model is proposed in UAIC. AB is a new immune model for remote sensing image processing, which contains many antibodies and memory cells of the same class. In remote sensing image classification, the memory cell decides the recognizing ability of the whole AB. UAIC utilizes the AB model to recognize a number of antigens (classified remote sensing image). The experimental results consistently show that the proposed UAIC has high classification precision and hence provides an effective option for intelligent remote sensing image unsupervised classification.

4.3.2 Supervised artificial immune classifier

A series of novel supervised artificial immune classifiers based on artificial immune systems has been proposed to perform remote sensing classification. The supervised artificial immune classifiers are based on the basic principles of immune recognition and immune memory in artificial immune systems. When a non-self-antigen invades the immune system, the immune system can adaptively recognize the antigen by the antibodies. After a body has successfully defended itself against the antigen, memory cells for the antigen are produced and remain in the immune systems. When the same or a very similar antigen invades the immune systems, the body’s response is much more rapid and powerful by using these memory cells. By simulating the process of immune recognition, the supervised artificial immune classifiers evolve the immune models or immune networks using the samples of regions of interest and obtain the memory cells or the memorial immune network to classify remote sensing imagery. Based on the above principles, the thesis proposes three supervised artificial immune classifiers. (1) A resource-limited classification algorithm of remote sensing images (RLCRSI) (Zhong et al., 2007), a new intelligent classification approach, using the resource-limited method to decrease the computational costs of classification and which can obtain the optimal centers of classification. Hence, RLCRSI may improve the classification accuracy, with a reasonable computational time. (2) In Pal (2008), an artificial immune-based supervised classification algorithm for land-cover classification. This classifier is inspired by the human immune system and possesses properties similar to nonlinear classification, self/non-self identification, and negative selection. Landsat ETM+ data of an area lying in Eastern England near the town of Littleport are used to study the performance of the artificial immune-based classifier. A univariate decision tree and maximum likelihood classifier were used to compare its performance in terms of classification accuracy and computational cost. Results suggest that the artificial immune-based classifier works well in comparison with the maximum likelihood and the decision-tree classifiers in terms of classification accuracy. The computational cost using the artificial immune-based classifier is more than the decision tree but less than the maximum likelihood classifier. Another data set from an area in Spain was also used to compare the performance of the immune based supervised classifier with the maximum likelihood and decision-tree classification algorithms. Results suggest an improved performance with the immune-based classifier in terms of classification accuracy with this data set also. Finally, a comparison with a back-propagation neural network suggests that the neural network classifier provides higher classification accuracies with both data sets, but the results are not statistically significant. (3) A novel supervised classification algorithm based on a multiple-valued immune network, which is a novel artificial immune network model, namely a multiple-valued immune network classifier (MVINC), to perform remote sensing image classification (Zhong et al., 2007). The multiple-valued immune network model is different from the traditional model, being formulated on the analogy with the interaction between B cells and T cells in the immune system. Therefore, the model has a property that resembles immune response quite well. MVINC inherits multiple-valued logic computational capability and the memory property of a multiple-valued immune network and can recognize the same or similar antigens quickly at different times. Therefore, MVINC has high classification accuracy.

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摘 要: 本研究对SPOT5/MODIS数据进行处理，探索了高光谱遥感数据的多种应用，例如分类、特征提取和图像融合等。关键词：高光谱遥感，数据处理，图像融合，分类。