Comparation and Analysis Methods of Moderate -resolution Satellite Remote Sensing Image Classification

Jinli Chen[1,2], Ming Luo [3] , Li Li[1],Daoliang Li[1], Chao Zhang[1*], Yan Huang[1] , Yijun Jiang [3]
1. College of Information & Electronics Engineering, China Agricultural University, Beijing 100083, China;
2. School of the Earth Sciences and Resources, China University of Geosciences, Beijing, 100083, China;
3. Land Consolidation and Rehabilitation Center, the Ministry of land Resources, Beijing 100035, China
*Corresponding author: Chao Zhang (Dr.) Tel: +86-10-62737855, Email: zhangchao_bj@163.com

Abstract: - Moderate resolution remote sensing images provide broad spectrum, high spatial resolution, and rich texture information. However, most traditional classification approaches are based exclusively on the digital number of the pixel itself. Thereby only the spectral information is used for the classification. But some researches have shown that pixel-based approaches for classification of remotely sensed data are not very suitable for the analysis of moderate resolution images.In order to get a reasonable planning and effective management of land cover,the paper provide a new classification and extraction method .In this paper, the object-oriented image classification technology is used in the experiment of land cover information extraction for CBERS-01 data, and compared with the results of the pixel-based approaches . The results show that the Object-oriented technique is a more suited method for moderate-resolution remote sensing image classification and a better classification results .

Key-Words: Object-oriented, moderate-resolution, CBERS-01, land cover, classification

1 Introduction

Land is important constituent in the ecosystem, land use and land cover change may cause the whole world environmental variation, the land cover change already becomes important one of studying global change. Land use and land cover information got by remote sensing technology is the main technique of land surveying and monitoring. Selecting the type of remote sensing images in research requires combination with the purpose of the study and the size of the region. Medium-resolution Satellite image conform to requirements of the study of the land cover classification in spatial resolution, phase, and economic, such as TM, SPOT2, SPOT4 and CBERS-01[1][2][9].At present, traditional pixel-based classification methods are used for classification of the moderate-resolution remote sensing images that provide spectrum information, high spatial resolution and plenty of spatial structure information. And spectral information is applied by traditional methods only[10].Many studies are done: Using multi-temporal Land sat TM data from the same growing season for the classification of land cover types in the south-western portion of the Argentine Pampas was explored by Guerschman [3];Remote sensing data, such as TM image is used for classification of landscape ecology which was investigated by Wang Y.[4]; Image information processing methods and professional potential applications through the CBERS-01 data which is used in the typically study of the satellite remote sensing surveillance systems of the environmental changes in the Liaodong area was studied by Liu Y.[5]; Using CBERS-1 CCD data, the BoHai Sea as the test areas and technology application of coastal and marine environmental remote sensing monitoring is proposed by Li S.[6];The use of CBERS-02 CCD data as an information source of the land use remote sensing survey, an application research through the studying of the image processing, image classification and the method of automated information extraction is presented by Li Y.[7]; A typical area of Nanjing site of CBER-01 CCD data is chose as the study area and mixed iterative analysis is adopted for the experiment of water body information extraction is researched by S. Zhao[8]. TM、SPOT and CBERS-1 are used to extract the thematic information to improve the classification accuracy and the decision tree extraction method on residential area were selected by Xiao P.[12].A new technique to solve the problem of bridge recognition from TM images is presented by Wu H.[13].The traditional classification methods fail to make full use of the information of the spatial structure.The research provides extraction method using the moderate-resolution remote sensing images, e.g. CBERS-01. This paper proposes object-oriented classification technology, analyzes the experimental results and contrastes with the traditional classification method, and then chooses a suitable method for the moderate resolution remote sensing images classification.

2 Study area and data source

The study area is Changping District which located in north of Beijing, China, at the confluence of the Jumna river, covering approximately 1352 km^2. The geographic coordinates (latitude/longitude) approximately range from 115°50′17″ E to 116°29′49 E″ , 40°2′18″ N to 40°23′13″ N , This area is characterized by rolling topography and flourishing vegetation.

CBERS-01 images, acquired on 10 October 1999, 10 June 2003 without any clouds/hazes, are used in this study. A CBERS-01 image has five multi-spectral bands, red, green, blue-green, near-infrared band, and panchromatic band, with 19.5-metre spatial resolution. Both dates of imagery were geo-referenced to a Transverse Mercator projection and Krasovsky spheroid with an RMSE of 1 pixel. It was necessary to radio metrically normalize the multiple dates of remote sensor data even though they were obtained on near anniversary dates.

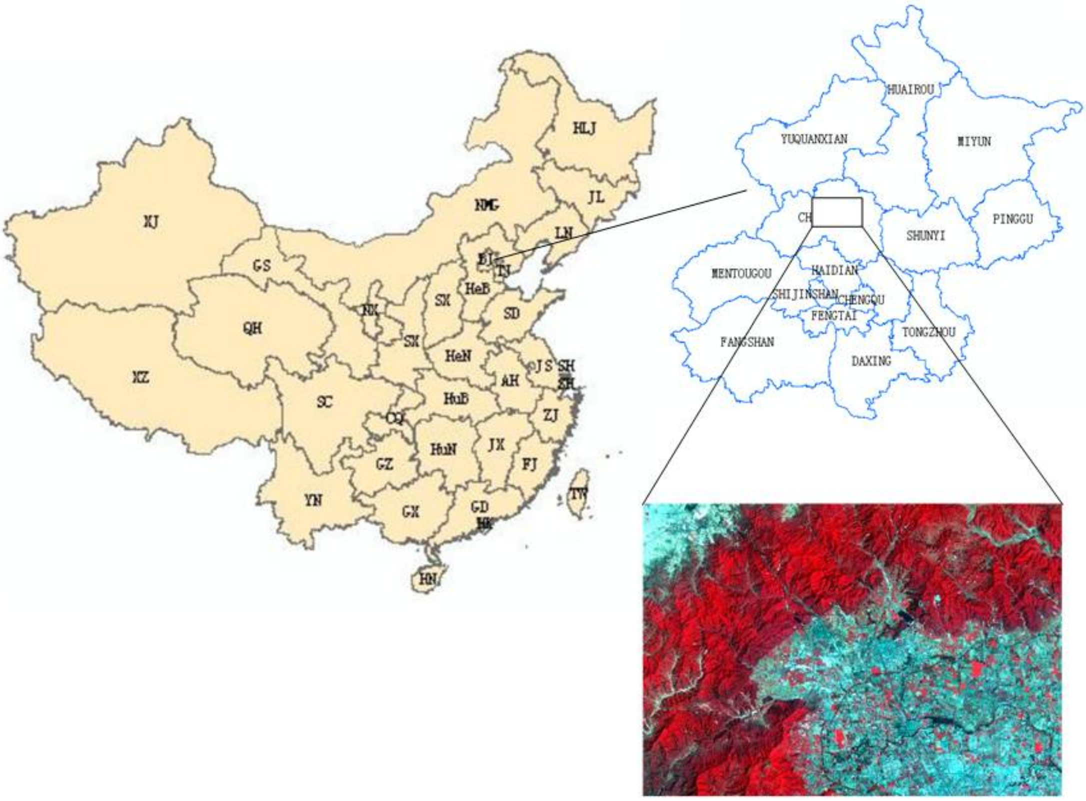


Fig1.Study site in Changping of Beijing from a CBERS-01 imagery in 2006

3 Methodology

3.1. Traditional of Pixel-based classification method

The traditional pixel-based classification method has been matured in the field of technology ,including unsupervised classification and supervised classification. Unsupervised classification is a bottom-up data-driven approach, while the supervised classification is the top-down knowledge-driven method, which must finish training before the classification. The typical supervised classification methods include parallelepiped, minimum distance, Mahalanobis distance, maximum likelihood method and the spectral mapping perspective. As for the precision of classification, these methods are appropriate for medium or low spatial resolution remote sensing image interpretation. Maximum Likelihood Classification (MLC) is the most common and high precision supervised classification method in the traditional classification method, which has the solid theoretical foundation, the clearly ability of the parameters settings, easily integration with the prior knowledge, and the advantages of a simple algorithm as well. The statistical character of remote sensing data is used by MLC, which assumes that various types of distribution function has the normal distribution and forms elliptical or ellipsoid distribution in multi-variable space, then the image is judged by the maximum likelihood discrimination rules that can get a higher accuracy classification results. However, spectral information is only used by MLC, the broad spectrum, higher spatial resolution, and rich information is neglected, so object-oriented classification technology is imposed to extract the land cover information.

3.1.1. Maximum Likelihood Classification Algorithm

The aforementioned classifiers were based primarily on identifying decision boundaries in feature space based on training class multispectral distance measurements. The maximum likelihood decision rule is based on probability[].

1) It assigns each pixel having pattern measurements or features X to the class i whose units are most probable or likely to have given rise to feature vector X.
2) In other words, the probability of a pixel belonging to each of a predefined set of m classes is calculated, and the pixel is then assigned to the class for which the probability is the highest.
3) The maximum likelihood decision rule is still one of the most widely used supervised classification algorithms.

The maximum likelihood procedure assumes that the training data statistics for each class in each band are normally distributed (Gaussian) (Fig.1). Training data with bi- or n-modal histograms in a single band are not ideal. In such cases the individual modes probably represent unique classes that should be trained upon individually and labeled as separate training classes. This should then produce unimodal, Gaussian training class statistics that fulfill the normal distribution requirement. Maximum likelihood classification uses the estimated Gaussian distribution to calculate the posterior probabilities for each class, and assigns a new pixel to the class with the highest posterior probability.

The estimated probability density function for class is computed using the equation:

$$P(x \mid \omega_j, \theta_j) = \frac{1}{(2\pi)^{1/2} \left|\sum_i\right|^{1/2}} \exp\left(-\frac{1}{2}(X - M_i)^T \sum_i^{-1} (X - M_i)\right) \quad \ldots\ldots \quad (1)$$

discriminant function：

$$g_i(x) = \ln(P(\varpi_i)) - \frac{1}{2}\ln\left|\sum_i\right| - \frac{1}{2}(X - M_i)^T \sum_i^{-1} (X - M_i) \quad \ldots\ldots \quad (2)$$

M_i is the estimated mean of all the values in the training class, and $\sum_i$ is the estimated variance of all the measurements in the class

$$M_i = \frac{1}{n_j}\sum_{k=1}^{n} x_{jk} \qquad (3)$$

$$\sum_i = \frac{1}{n_j}(x_{ij} - M_i)^T (x_{ij} - M_i) \qquad (4)$$

n_j is the number of training samples, x_{jk} is the Eigenvector of training samples.

Maximum Likelihood criterion：

$$g_i(x) = \max_{j \in n} g_j(x) \qquad (5)$$

Since the log of the probability is a monotonic increasing function of the probability, the decision can be made by comparing values for each class as calculated from the right hand side of Maximum Likelihood criterion.

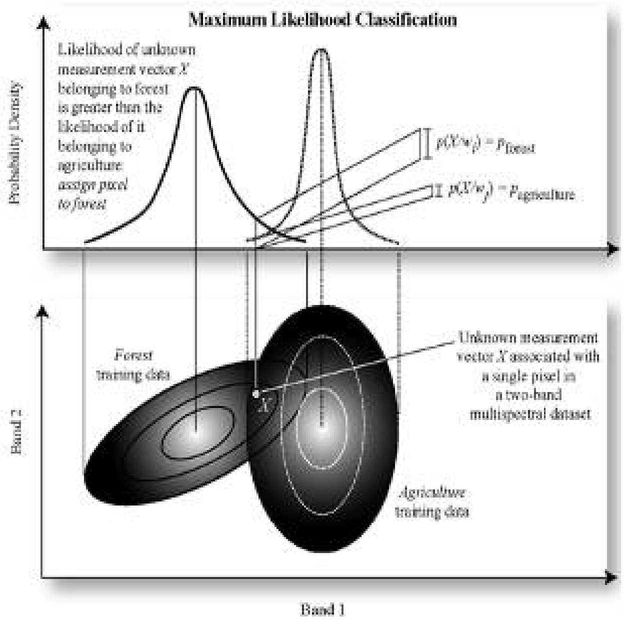


Fig.2 Maximum Likelihood Classification

3.1.2. Minimum Distance Classification Algorithm

The minimum distance to means decision rule is computationally simplely and commonly used. When used properly it can result in classification accuracy comparable to other more computationally intensive algorithms ,it requires that the user provide the mean vectors for each class in each band from the training data. To perform a minimum distance classification, a program must calculate the distance to each mean vector from each unknown pixel. It is possible to calculate this distance using Euclidean distance based on the Pythagoreantheorem（Fig.2 a）or round the block distance measures（Fig.2 b）.

1.Euclidean distanc

$$Dist = \sqrt{\sum_{i=1}^{N}(x_i - M_{ij})^2} \qquad (6)$$

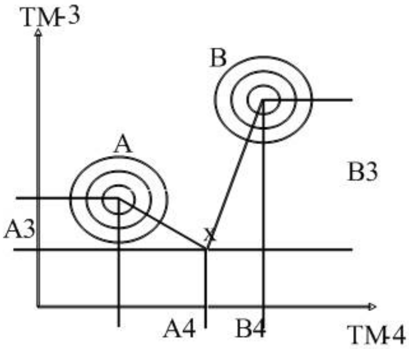
classification： $j = 1,2,...m;$； band： $i = 1,2,...n;$

$x_i = (x_1, x_2, ...x_n)$ ， $M_{ij} = (m_{1j}, m_{2j}, ...m_{nj})$

2.round the block

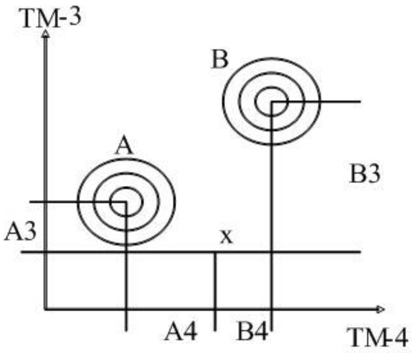
$$Dist = \sum_{i=1}^{N}\left|(x_i - M_{ij})\right| \qquad (7)$$

$x_i = (x_1, x_2, ...x_n)$ ， $M_{ij} = (m_{1j}, m_{2j}, ...m_{nj})$



$$\sqrt{A_3^2 + A_4^2} < \sqrt{B_3^2 + B_4^2}$$

（a）Euclidean distanc



$$A_3 + A_4 < B_3 + B_4$$

（b）round the block

Fig.3 Minimum distanc Classification

3.2. Object-oriented classification method

Classification is the process of connecting the classes in a class hierarchy with the image objects in a scene. After the process of classification, each image object is assigned to a certain (or no) class and thus connected with the class hierarchy. With the assignment of a class to an image object, the relations to other classes formulated in the specific class description are transferred to the image object[16]. The result of the classification is a network of classified image objects with concrete attributes, concrete relations to each other and concrete relations to the classes in the class hierarchy.

Limitations of the basic classification and pixel units is broke to, and more semantic information to a number of adjacent pixels of the object (including higher object and the object) is used to be the processing units, then remote sensing image classification and objectives of the feature extraction are achieved a higher level . The characteristics of the spectrum, more of structure geometric structure information, such as shape, color and texture are used by Object-oriented classification. Objects are composed by the same characteristics pixels and classified base on the characteristics of each object. Two key works must to be done by Object-oriented image classification: image segmentation and classification.

3.2.1. Image Segmentation

In order to obtain image object primitives as basic processing units, the object oriented approach to image analysis requires complete segmentation of an image. In image segmentation the expectation is in many cases to be able to extract the desired area of interest in an image for a certain task.segmentation of an image into a given number of regions is a problem with an astronomical number of possible solutions and in many cases regions of interest are heterogeneous/ambiguities arise and the necessary discerning information is not directly available.Therefore, a rough overview is given of the most common bottom-up approaches to image segmentation(Fig.3).In bottom-up approaches the segments are generated based upon a set of statistical methods and parameters for processing the whole image. As such, bottom_up methods can also be seen as a kind of data abstraction or data compression.They group pixels to spatial clusters which meet certain criteria of homogeneity and heterogeneity. The two image objects with the smallest increase of the heterogeneity is merged in each step. The segmentation procedure stops when the smallest increase exceeds a specified threshold.

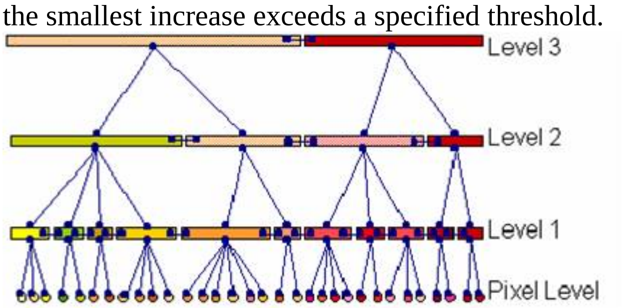


Fig.4 Process of Image Segmentation

3.2.2. Image classification

. Objects are composed by the same characteristics pixels and classified base on the characteristics of each object.A class is a category of image objects.It can both be used to simply label image objects or to describe its semantic meaning[17].Classification is a procedure that associates image objects with an appropriate class labeled by a name and a color. Information contained in image objects is used as a filter for classification.Based on this,image objects can be analyzed according defined criteria and assigned to classes that best meet these criteria. The classes can be grouped in a hierarchical manner allowing the passing down of theirdefining class descriptions to child classes using the inheritance hierarchy. Classic classifiers in remote sensing are Nearest Neighbor Algorithm, membership function.

1.Nearest Neighbor Algorithm

In the Nearest Neighbor method , both describing of the various classes 、feature space definition and forming of knowledge base structure are all finished by mean of layers, and then representative land is picked as samples, and each class were given appropriate representative of the target surface features, classification is Completed finally. At first , training samples which have already classified was carried to hyperspace, then put non-classified samples into the hyperspace too, and Calculation the distance between non-classified samples and all training samples. If one samples in the Nearest Neighbor, the non-classified sample is judged to the classification. The distribution of all classification is determined by degree of relation or possibility. the shorter distance between sample and image is, the bigger degree of relation is.Many distance can be used in the hyperspace and Euclidean distance is usually adapt , Algorithm is as follows publicity:

$$d = \left[\sum_f \left| \frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f} \right| \right]^{1/2} \qquad (8)$$

d is the distance between sample s and image o ;
$v_f^{(s)}$ is the eigenvalue about the Characteristic of sample f; $v_f^{(s)}$ is is the eigenvalue about the Characteristic of image f; σ_f is standard deviation;

2.Incorporating Ancillary Data in the classification

After Multiresolution Segmentation, the basic of the image is not a single pixel but polygon which is composed of the homogeneous pixel. To each polygon object, it can calculate spectral information of the included pixel, polygon shape information, texture information, position information and topological information .Specific classification rules can take full advantage of the various information which is provided by the objects to combine and extract the specific land feature. An analyst photo-interpreting a color aerial photograph of the terrain often has at his or her disposal (1) systematic knowledge about the soils, geology, vegetation, hydrology, and geography of the area, (2) the ability to visualize and comprehend the landscape’s color, text, height, and shadows, (3) the ability to place much of this diverse information in context to understand sites conditions and associations among phenomena, and (4) historical knowledge about the area. Ancillary dates are any type of spatial or non-spatial information that may be of value in the image classification process, including elevation, slope, aspect, geology, soils, hydrology, transportation networks, political boundaries, and vegetation maps. The accuracy and quality of remote sensing-derived land cover classification can be improved by incorporating ancillary data in the classification process. Ancillary dates can intervene at different levels and forms (logical judgment or physical parameters, mathematical expressions and so on), it is flexible for the integration between the remote sensing and the knowledge of earth sciences. In classification function, expert knowledge and pertinent data of RS and other information can be continuously added in the level structure to improve the classification conditions and the classification accuracy.

This paper base on the RS image interpretation, take terrain parameter as Supplementary Information of classification, DEM factor as the band of unspecified image is added, build a new unspecified image, and expand the parameter definition of feature space, and then classify by Object-Oriented Method. At first, slope must be calculated from DEM, and then the slope will act as constraint rule for further classification of the image.

Slope data calculating:

At first, Triangular Irregular Network (TIN) is created with the study area 1:50000 relief contour data. The second, the Digital Elevation Model (DEM) is interpolated with the discrete elevation points in the TIN. The DEM spatial resolution is 10 meters.

The DEM is the base data resource. The 3×3 analysis is adopted and the pixel rate of elevation
change in x and y direction are computed with 8 neighboring pixels which illustration is shown as Fig. 5.

e_5	e_2	e_6
e_1	e_0	e_3
e_8	e_4	e_7

The pixel e_0 elevation change rate in x and y direction are computed with equation (9) and (10):

$$Sl_x = \frac{(e_8 + 2e_1 + e_5) - (e_7 + 2e_3 + e_6)}{8D} \tag{9}$$

$$Sl_y = \frac{(e_7 + 2e_4 + e_8) - (e_6 + 2e_2 + e_5)}{8D} \tag{10}$$

The quadratic curved surface fitting with which the max slope of the pixel is computed is used to compute the slope. The slope of one point on the land surface is the function of the elevation change rate in the x and y direction of the land curved surface function $z = f(x, y)$. That is the Equation (11).

$$slope = \arctan \sqrt{Sl_x^2 + Sl_y^2} \tag{11}$$

3.2.3. Technique Process of Object-oriented classification

The general steps of Object-oriented image classification method as follows: (1) Multi-scale segmentation; (2) Image feature extraction (including image spectral characteristics, shape features, topological characteristics, texture characteristics and so on) (3) classification rules expression (4) Image classification (5) Output the results. Flow chart of object-oriented approach for sensing images classification is described as follows (Fig.5):

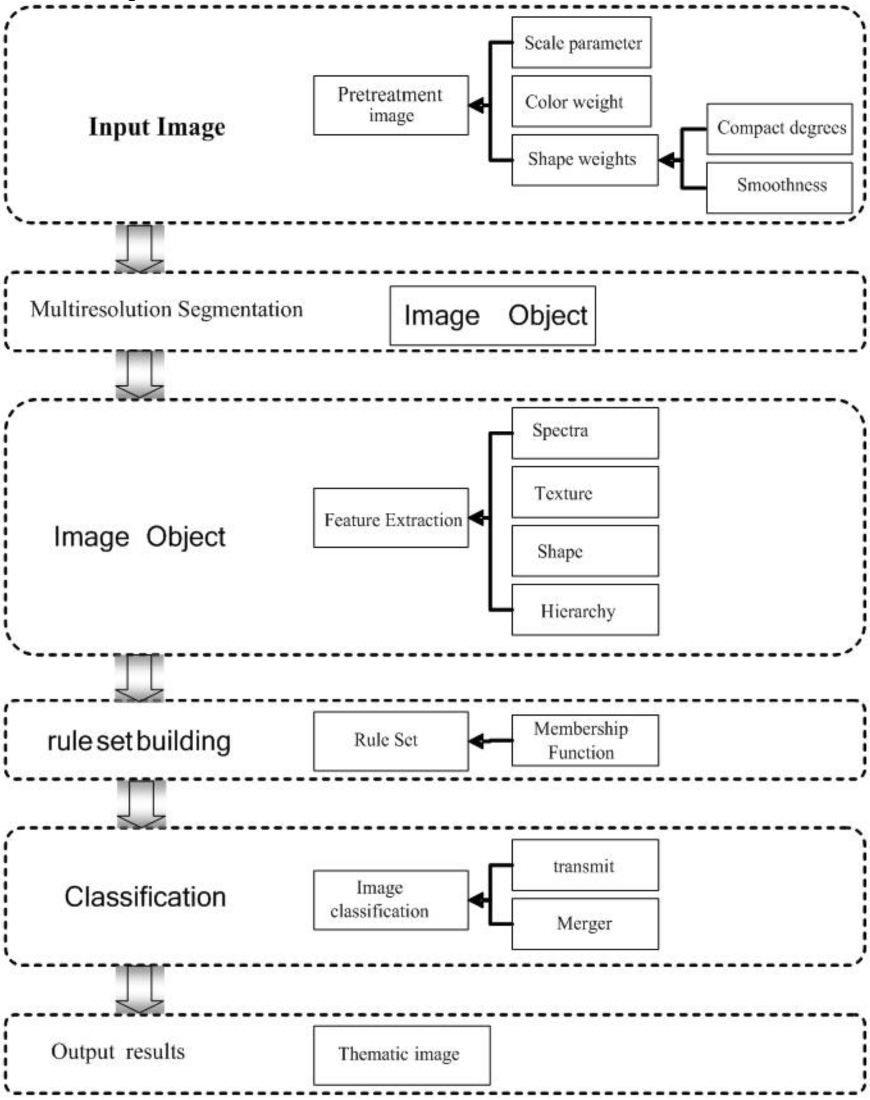


Fig.6 Object-oriented classification Technique Process

4. Experimental Analysis

4.1 Contrast Experimental Results

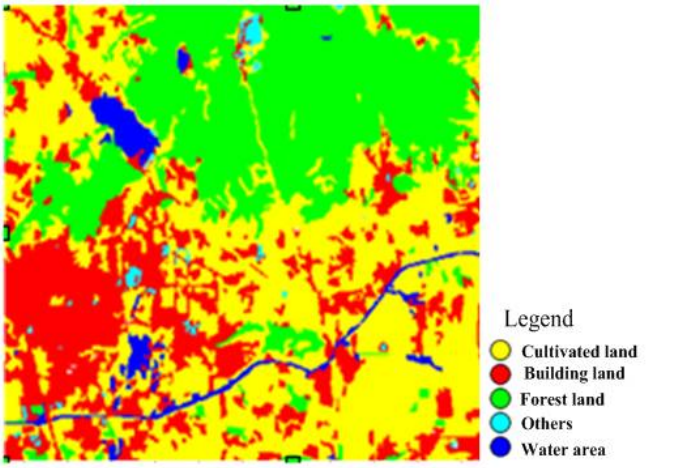
Firstly, an experimental area is cut from original image for convenience image processing,which includes Cultivated land, Forst land, Building land, Water area and others.The image segmentation must be completed before classification. In this study, the eCongnition is applied to image segmentation, the segmentation scale and shape factor are respect set as 20 and 0.1, while the Smoothness and denseness are set as 0.7 and 0.3. The experimental area segmentation image as follows:

(a) Level 1 (Scale Parameter 15)

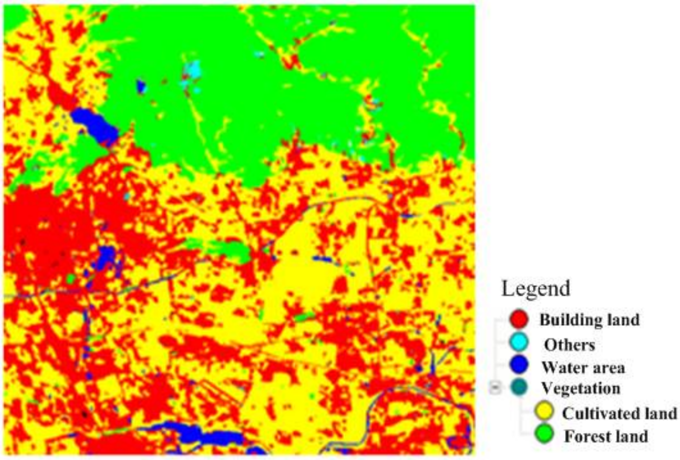
(b) Level 1 (Scale Parameter 30)

Fig.7 Multi-resolution image segmentation

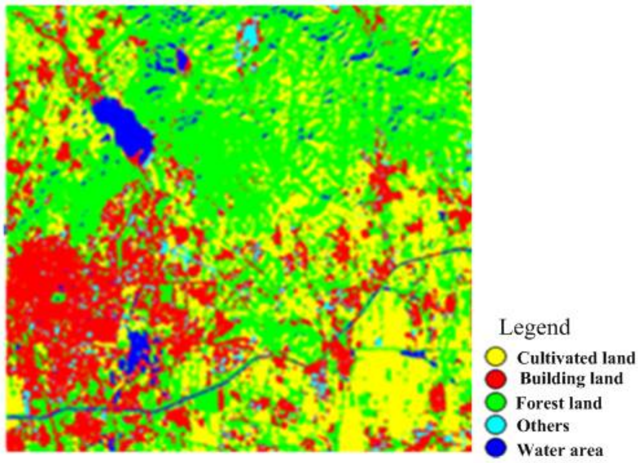
In this research, Object-oriented classification is used to experiment in the Changping district of Beijing by eCognition software, the results are contrasted with traditional classification 's.



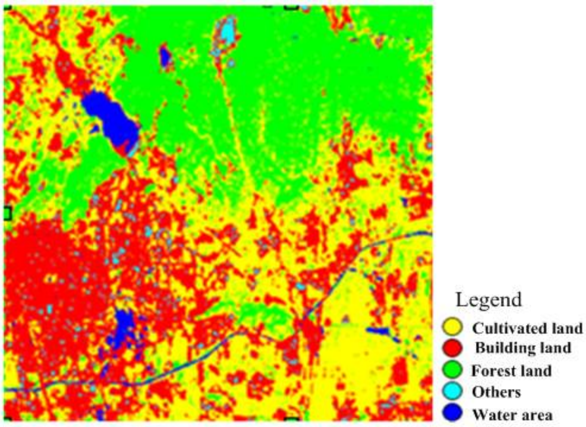
(a) Nearest Neighbor Classification



(b)Incorporating Ancillary Data in the classification



(c) Minimum Distance Classification



(d) Maximum Likelihood Classification
Fig.8 Comparation of all classification results

4.2. Contrast Experimental Results

Table 1, Table 2, Table 3 and Table 4 show the Confusion Matrix of Object-oriented Classification based on the thematic knowledge, Nearest Neighbor Algorithm, Minimum Distance Classification and Maximum likelihood classification. And then contrast accuracy of each class about Object-oriented Classification and MLC(Table.5)

Table1 Confusion Matrix of Object-oriented Classification based on the thematic knowledge (Overall Accuracy= 97.80%, Kappa=0.9694)

Sample / Classification	Farmland	Forestland	Building site	Water	Other site
Farmland	11770	1216	490	54	85
Forestland	63	14794	0	0	23
Building site	367	86	10830	84	22
Water	6	12	2	3835	0
Other site	0	0	118	5	687
total	12206	16108	11456	3978	817

Table2 Confusion Matrix of Nearest Neighbor Algorithm (Overall Accuracy=94.06%, Kappa=0.9177)

Sample / Classification	Farmland	Forestland	Building site	Water	Other site
Farmland	11770	1216	490	54	85
Forestland	63	14794	0	0	23
Building site	367	86	10830	84	22
Water	6	12	2	3835	0
Other site	0	0	118	5	687
Total	12206	16108	11456	3978	817

Table3 Confusion Matrix of Minimum Distance Classification (Overall Accuracy=79.29%%, Kappa=0.7093)

Sample / Classification	Farmland	Forestland	Building site	Water	Other site
Farmland	11943	2235	80	0	0
Forestland	4041	9334	262	43	10
Building site	486	0	9619	22	364
Water	0	593	10	2480	0
Other site	130	0	546	0	407
Total	16600	12162	10517	2545	781

Table 4 Confusion Matrix of MLC (Overall Accuracy=88.94%; Kappa=0.8427)

Sample / Classification	Farmland	Forestland	Building site	Water	Other site
Farmland	14835	1962	78	11	3
Forestland	898	10185	0	21	0
Building site	788	2	9945	39	323
Water	0	13	2	2474	0
Other site	79	0	492	0	455
Total	16600	12162	10517	2545	781

Table 5 Comparision of Accuracy

Classification	Classification Accuracy (%)				
	Farmland	Forestland	Building site	Water	Other site
Object-oriented	89.37	83.74	94.56	97.21	58.26
MLC	96.43	91.84	94.54	96.41	94.54

The results in the (c) and (d) show that the phenomenon of salt-pepper exists in classification of MLC(Fig. 8). There is seriously wrong classification between the farmland and forestland, the forestland shadow and water. the Kappa of object-oriented classification (Table 2) is 0.9177, the overall accuracy is 94.06%, while the Kappa and overall accuracy of the MLC(Table 4) is only 88.94%.

For each class of land(Table 5), The classification accuracy of the farmland and water is better by using Object-oriented classification technology, which can achieve 96%, and that of forestland is 91.84%, classification accuracy of the Building land is 94.54%, and classification accuracy of the others is 94.06 %(Table 2).The accuracy of object-oriented classification is better than the MLC. The results show that the wrong classification in farmland and forest is improved greatly by using object-oriented classification, the map-spot is comparative integrated, and the phenomenon of salt-pepper performance is obviously reduced. Wrong classification in mountain shadow and the others is also obviously improved, the classification results are obviously better than the classification method based on pixels.

5. Conclusion and Discussion

This research uses CBERS 01 data to extract the land cover/land use information, compares the traditional method with the Object-Oriented information extraction technology, and then makes the following conclusion:

(1) Object-oriented classification technology is not only suitable for high resolution remote sensing data, but also applicable for moderate-resolution remote sensing images.

(2) For the CBERS 01 data, the object-oriented classification is better than MLC, and obtains higher classification accuracy.Object-oriented classification has more characteristics are involved in, and could be added to other topic knowledge, such as DEM, so this classification is more flexible and significantly and higher accuracy.

(3)CBERS 01 data can represent land cover information better.The results extraction based on CBERS-01CCD data as information source is suitable for the accuracy requirements of 1:100000, so CBERS-01 data can be used for land cover / land use surveys and monitoring on 1:10 million.

This technology of land cover information extraction based on CBERS-01CCD data can work on the research of the application of moderate resolution remote sensing data in larger scope of region, especially the land surveys and monitoring. This technology program proposes the necessary technology foundation for the application of next CBERS-02 CCD data in land sources surveys and monitoring.

Acknowledgements:

This research is funded by the National High Technology Research and Development Program of China titled ‘Land Consolidation Remote Sensing Monitoring Technique and Application’ (project contract number: 2006AA12Z129).

References:

[1] Kazuhito J. T. Maruyama,M.L. Multi-temporal analysis of deforestation in Rondoˆnia state in Brazil using Landsat MSS, TM, ETM+ and NOAA AVHRR imagery and its relationship to changes in the local hydrological environment[J]. *International Journal of Remote Sensing,* No.22, 2003, pp. 4467–4479

[2Cabral, A. Devasconcelos, M.J. P. Multi-temporal compositing approaches for SPOT-4 Vegetation[J]. *International Journal of Remote Sensing*, No. 16, 2003, pp.3343–3350

[3] Guerschman, J. P. Paruelo, J. M. Land cover classification in the Argentine Pampas using multi-temporal Landsat TM data[J], *International Journal of Remote Sensing*, Vol.9,2003, pp.3381-3402.

[4] Wang, Y. Shen, B. Application of Remote Sensing technology to Land use/cover change [J]. *Journal of China University of Geosciences*, Vol.4, 2001, pp.36-38.

[5] Liu,Y. Evaluation of Satellite CBERS-1 Applying to environmental monitor in Eastern Liaoning Province[J], *Science of Surveying and Mapping*, Vol.15, 2000,pp.30-33.

[6] Li, Y. Liu, Z. The Application of CBERS-02 Remote Sensing Image in the land use change dynamic monitoring[J], *International Journal of Remote Sensing*, Vol.33, 2003,pp.66-72.

[7] Zhuo, J. Zhao, D. Accuracy assessment methods of classification results of land use monitoring based on CBERS-02 satellite image[J], *Science of Surveying and Mapping*, Vol.32 No.6, 2006,pp.34-37.

[8] Zhao, S. Traction of Lake information from Nanjing image through China-Brazil Earth source satellite No.1(CBERS-1)[J], *Lakes Science, 2001,pp.280-284.*

[9] Steinnocher, K. T. Kressl, F. P. Land cover characterization and change detection for environmental monitoring of Pan-Europe[J]. *International Journal of Remote Sensing*, vol. 6 &7, 2002, pp.1159–1181.

[10] Maingi, J. K. Marsh, S. E. Assessment of environmental impacts of river basin development on the reverie forests of eastern Kenya using multi-temporal satellite data[J], *International Journal of Remote Sensing,* vol.22, 2001 ,pp.2701–2729,

[11] Bao, M. Classification of Multi-Temporal Sar Images and Insar Coherence Images using Adaptive Neighborhood Model and Simulted Annealing Approch[J], *International Journal of Remote Sensing*. Vol. 8, 2002, pp. 1669-1675.

[12] Xiao, P. Liu, S. Methods and Accuracy assessment for land use and cover classification based on medium resolution remotely sensed data[J], *Remote Sensing for land& resources.* Vol.4, 2004, pp.41-45

[13] Wu, H. Liu, Z. A study of bridge recognition from Landsat TM images[J]. *Journal of Remote Sensing,* Vol.6, 2003, pp.479-484

[14] Luo, Y. Zhu, J. An Application of CBERS Data in the Forest Resources investigation of Guizhou Province[J].*Journal of Nanjing Forestry University(Natural Sciences Edition).* Vol. 29, 2005, pp.92-94

[15] LI, X. Jing, H. Landscapes classification of Ebinur lake basin based on CBERS-2RS imagines[J]. *Journal of Arid Land Geography.* Vol. 30, 2007, pp.737-741

[16] Kong, C. Xu, K. Classification and extraction of Urban Land use information from High-Resolution image based on Object Multi-features[J]. J*ournal of China University o f Geosciences*,.Vol.17, 2006, pp:151-157

[17] Antonio, J. Parallel techniques for information extraction from hyperspectral imagery using heterogeneous networks of work stations[J]. *Journal of Computer*. Vol. 68, 2008, pp.93-111

[18]Xiao, X. Boles, S. Landscape scale characterization of cropland in China using Vegetation and Landsat TM images[J]. Journal of remote sensing, no. 18, 2002, pp. 3579–3594