Land cover automatic classification based on RS-Informatic Tupu

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Abstract: The importance of the extraction and cognition of geo-information has been increasingly highlighted in the face of the massive accumulation of remote sensing data and the lack of application information. According to the geo-informatics Tupu methodology regarding the visual cognitive process, Tupu-cognition can automatically interpret remotely sensed imagery. In this study, using a unified framework of geographic information systems, we extract the features of images step by step. Spatial-spectrum a nalysis is then executed in the geo-cognitive process described as "Perceive-Identify-Confirm". Algorithms like multiscale s egmentation, feature analysis, and supervised learning are invoked to meet the application's requirements for automation and intelligence. In the cognitive application of land-cover information, we first establish the mechanism of prior knowledge management for automation. Second, a number of machine learning algorithms are employed to improve the intelligence. Finally, adaptive iteration is introduced to optimize the results. The data selected for this classification experiment are Advanced Land Observing Satellite (ALOS) multispectral images in the Pearl River Delta. The land cover results are consistent with expectations and illustrate the f easibility of our method.

Key words: Tupu-cognition, automatic interpretation, land cover, automatic classification

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1 INTRODUCTION

With the improvements in spatial resolution of remotely sensed imagery, and the challenges of digital communication and the Internet network, the processing of remotely sensed information is gradually being replaced by quantitative integration technology. However, a mapping technology process that is fully d igital and provides highly automated classification of remote sensing data has not yet entered the mass production stage, so the ability is lacking for real-time processing of massive amounts of data and multidate data. Existing technology is far from what will be required to address global change, regional sustainable development research, and to take advantage of remotely sensed data quickly with coverage over large areas (Chen, 1997; Quartulli, 2013). As early as the 1990s, Chen proposed the concept of geo-informatic Tupu and landscape reality signs of figures interpreted inversely from massive data, the main source of which is remote sensing with its unique earth observation advantages. Therefore, the theory of using remotely sensed imagery for Tupu cognition and calculation, put forward by Luo, demonstrates the design of a remote sensing Tupu computing platform on two l evels—pixel-level and object-level (Chen, 2004; Luo, 2009). At the same time, Tian, et al. (2003) agreed that utilizating Tupu could improve the accuracy of classification and the discovery of new knowledge with automatic interpretation of remotely sensed imagery. The research by these authors have promoted problem solving on how to extract useful information from massive a mounts of remotely sensed data automatically and intelligently, and to identify the underlying geology and natural laws to better guide social practices(Datcu,2005).

Land cover information is what is mainly provided by r emotely sensed data, as well as basic information about the earth's surface for various applications. With the massive amounts of remotely sensed data, many projects seeking to extract land cover information have been carried out using computer-dominated and artificial auxiliary technology (Homer, 2004; Friedl, 2010). But these have failed to achieve full automation (being limited by the steps necessary for selecting samples) and higher extraction accuracy. For example, the TWOPAC automatic classification process proposed by Huth, et al. (2013) still demands that the user select samples for classification and validation. The land utilization classification method based upon a decision tree proposed by Hu, et al. (2013) also has low classification accuracy. Therefore, there is still a gap between automatic

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classification methods and the application of precise models, which are difficult to popularize and apply over a wide range.

With respect to much of today's artificial intelligence research, the process of computer-simulation of human cognition may ultimately pave the way to solving the stark asymmetry between data collected and information utilized. Cognitive psychology, optic nerve physiology, and computer vision cognitive models have made great strides in recent years. For example, the information processing theory derived by way of computer computing has become the mainstream orientation of cognitive psychological research (Best,2000; Pen,2004). The function of each unit of the brain's visual cortex and the gradual layered process of visual information have also been further confirmed by the introduction of the Functional Magnetic Resonance Imaging (fMRI) and other technologies. The deep learning theory based on hierarchical visual signals processing has also been recognized by many scholars (Hinton, 2006; Bengio, 2009). The gradual completion and realization of these research theories have promoted the formation and development of remote sensing Tupu cognitive methodology.

Based on the above research, the Tupu-cognition of remotely sensed imagery was developed in response to the real need for the extraction of geological information from remote sensing data. Tupu-cognition interrupts and extracts remote sensing information as data is being gathered, automatically and intelligently, much like the process of visual cognitive understanding. Itaims to identify the geological signs using Tupu, which can supply the technical support to fully take advantage of remote sensing data. For example, land cover information, supported by multisource data using Tupu-cognition of remotely sensed imagery and the conditions and application requirements of actual data, can now be automatically classified and quickly extracted over a wide range with good test results.

2 TUPU-COGNITIONOF REMOTELY SENSED IMAGERY

2.1 Tupu-cognition guided by geological informatics Tupu

Geological informatics Tupu is the analysis of composite features of "spatial pattern" and "time process" in geospatial systems and its elements and phenomena. This methodology realizes the intelligent cognition of earth information science (Ye, 2004). It can be classified into signs Tupu, diagnostic Tupu and implement Tupu according to the working process functions (Chen, 2000). Signs Tupu relates data directly, providing running results of information extracted from the model. It is the primary focus of the Tupu-cognition of remotely sensed imagery, providing the clues and basis for further study (Zhang, 2009).

Remote sensing is an effective means for obtaining surface information, the primary object of information extraction, while Tupu-cognition of remotely sensed data has tried to simulate the visual cognitive process in the brain, known as "Perceive-Identify-Confirm" to produce a geological signs figure automatically and intelligently. The key point is Tupu-coupled remotely-sensed imagery. As shown in Fig. 1, the management, display, and utilization of the various data, in the framework of a geographic information system, are in graphic form according to their geographic attributes. The main task in this process is to extract and manage multisource data. Next, in the first phase of Tupu-cognition, the instrument perceives the feature object, which requires both prior knowledge and the multiscale segmentation of actual images to determine the primary attributes of the feature (geographic distribution, spatial scale, etc). In the second phase the instrument identifies the specific feature objects proactively, which not only analyze the specific features of the objects (spectrum, shape, topography, time, interdependence) but also combines the image content with prior knowledge to actively and specifically learn, and to accumulate experience in distinguishing features. In the final phase the objects in the image are confirmed, labeling the image content by the cognitive results and also formulating graphic feedback for the geographic information system. Objects can be reviewed to improve accuracy by iteration, or can be stored as prior knowledge for later use. The primary task of this process is to generate a geological sign Tupu. Thus far, sign Tupu can be inputted into the models of various time-space analyses for further research, according to application requirements, and then generate geological diagnostic Tupu to guide its eventual implementation.

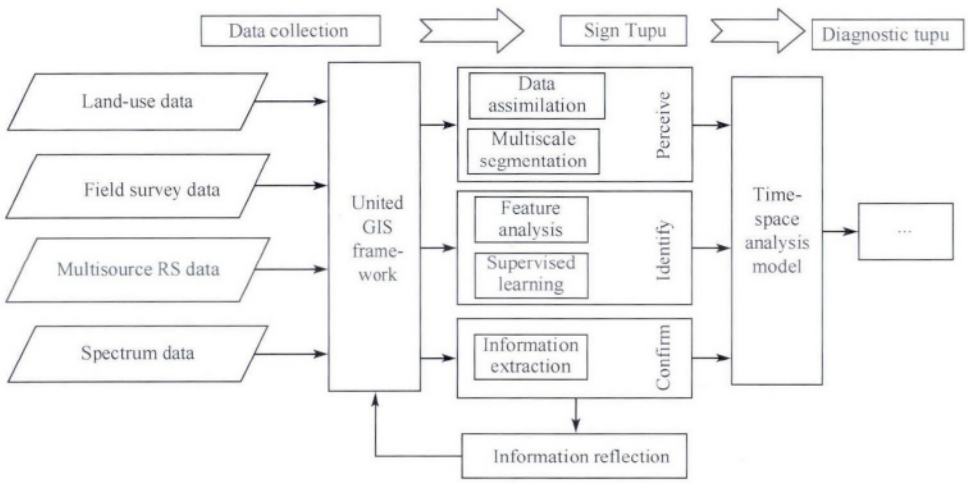

Fig. 1 Process of remotely-sensed Tupu-cognition

Analysis ofthe spatial-spectrum runs through the entire r emote sensing Tupu-cognition process in two main forms. The first is spatial analysis, which establishes relationships between features and their environment. It also contributes to the management of the distributed rules at the macro level with an o mnibearing investigation at different scales and degrees and using different reference systems. The second form is spectral a nalysis, which is helpful in the evolution from past to present and also in the reflection of different optical bands indeep feature research.

In the "Perceive" phase of the cognitive process, to cognize more knowledge by relying on "space" and acting on the level of "space", assimilation of different data according to geographic attributes is first required, even though various statistical data must be inputted in map form. Secondly multiscale segmentation may be regarded as spatial analysis based on the extraction of elements, corresponding to the traditional pixel as a cognitive unit, which can effectively manage spatially-continuous homogeneous pixel groups in remote sensing processing. It also carries more object characteristics and knowledge in the cognition perspective. It finally composes an unknown terrain map by elements, referring to object attributes. In the "Identify" phase, to cognize more Tupu-coupled knowledge, firstly the f eature element, formed by the effective extraction and expression analysis in the Tupu feature element, has closer contact with the feature target, and can serve as the basic unit for subsequent supervised learning and classification criteria. T he prior knowledge from supervised learning is also applied in the forms of "space" and "spectrum", such as feature spectrum, shape, texture and so on. The process of supervised classi-f ication is mainly to further process features and the sample is simply the carrier of all kinds of object features. Finally in the "Confirmation" phase, cognitive results are also stored and presented in the form of "space", which can perform many kinds of vector p rocessing operations with the geographic information system.

Data exist in the form of vectors or grids independently constrained by the framework of the geographic information s ystems, and at the same time the extraction and application of Tupu information is also limited by the finite analysis method. Also, the Tupu nature of the remotely sensed imagery as the main data source requires the analysis of Tupu to the degree possible, in order to realize the key to the whole cognition process— "spatial-spectrum" coupled analysis and the simulation of recognized figures to obtain the spectrum, and the translation of the spectrum to obtain the figure. This process excavates the progressive model of "pixel-element-feature-object" vertically and solves the question of "spatial-spectral" coupled features transversely, achieving the automatic interruption of remotely sensed information with the full play of prior knowledge, thereby exploring the potential of remotely-sensed imagery.

2.2 Application method ofautomatic interpretation of remotely-sensed information

For practical application, at least two application requirements must be satisfied concerning the automatic interpretation of remote sensing data. One is the automatic extraction of information, which is also required for massive amounts of remote sensing data for real-time (or quasi real-time) application. From the machine learning perspective, self-adaptation and self-learning are two criterion for machines to achieve this goal. Self-adaptation enables the machine to accomplish specific tasks without human intervention and self-learning enables the machine to extract more suitable information by taking the initiative to find knowledge. The second requirement is the extraction of intelligent information, which is also the basis for related industry applications. From the remote sensing application perspective, high a ccuracy and high fault tolerance are the two most important c riteria for the utilization of automatically extracted information from remotely sensed imagery. High accuracy is the reliable standard of remote sensing for a single application. High fault tolerance is the stable and available standard of remote sensing in business operations (Baraldi, 2012; Zhang, 2000).

With respectto technology and the automatic interpretation of remote sensing data and the practical requirements of land cover classification, we have designed a general process for e xtracting land cover cognitive information, and made preliminary explorations of the cognitive method in actual applications. As shown in Fig. 2, geographic information systems i ntegrate all kinds of data and information into a unified framework, consisting mainly of land-use data, terrain data, field i nvestigation data, typical feature spectrum data, and primary multisource remote sensing data. These data have been combined into one geographic reference to ensure that the auxiliary data and information corresponding to each pixel can be searched in a timely manner. These data must also attract elements upon a scale suitable for a multiscale segmentation algorithm in order to calculate all kinds of features (spectrum, shape, texture, terrain, environment condition, various indexes, and so on), which may require all kinds of secondary data for these calculations. This is the "Perceive" phase shown in the Fig. 2. Next is the application of all kinds of knowledge, the main point of the process of automatic sample selection. The analysis, on the other hand, points to the element features, especially the spectral features of typical object features, based on the corresponding type of land use in the early period to establish possible change and contact. Next is the "Identify" phase where in the spectrum is interpreted in order to recognize space, performing supervised classification of all elements assisted by a large number of samples. During this phase the p erformance of the classification model and the accumulation of experience distinguishes the model, achieving a suitable application for a large area. Finally the iterative classification is matched to the data and information under the framework of the geographic information system to complete the final "Confirm" phase. The fundamental goal for remote sensing Tupu-cognition is to obtain land cover information by automatic interpretation without consideration of subsequent algorithms such as-land-use analysis, Land-Cover of Change (LUCC) analysis, spatial-temporal analysis, and so on.

The key to the above process is the self-circulation of i nformation flow, the main difficulties of which are discussed b elow.

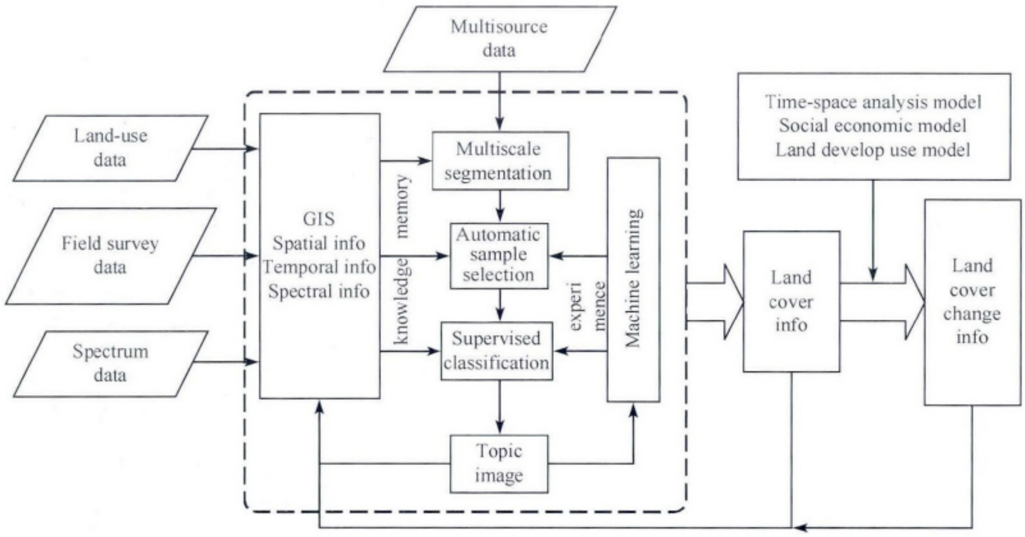

Fig. 2 Process of obtaining land cover information

2.2.1 Management of prior knowledge

The basis for automation is to have a certain understanding of the research objects; that is, it requires the existence of prior knowledge. The knowledge employed to assist in land cover classification can be divided into two types. One is the knowledge of the "figure" itself, whose typical indicator is former land use data recognizing the feature of a certain region from the spatial distribution and telling machine the "where" of this knowledge. It is most suitable for a machine to access this knowledge based on storage. The other type is the knowledge of "spectrum" with the typical features of data in a feature spectrum library with regard to the vegetable growth rule, which recognizes the possible appearance in the image of a certain object feature from the spectrum and a time series to tell the m achine the "how" of this knowledge. However, results from machine-based computing knowledge are much less comprehensive than those from the brain. How to make a machine combine and make full use of these two types of prior knowledge is related to both the automatic implementation of land cover classification and the accuracy of the final classification result. The former approach, as described above, is to know the object feature and its change laws in the specific location at a particular moment, such as a wasteland and the expansion of urbanization, the translation of farmland to town, and so on. These focus on the objective temporal continuity of an object feature and require spatial resolution of images to identify the image's characteristics and the expressive characteristics of the object's variety of f eatures. For example, the expression of water at the near infrared band is for strong absorption, while vegetation expresses high reflection. The area index of leaf growth shows rich changes in the time phase, and so on. The focus is on the consistency of the local regional object features and requires spectral resolution of the images. The initial purpose of employing the unified G eographic Information System (GIS) framework is to better manage these prior experiences with a current feasible method of storing, searching, and updating all knowledge based on these geographical properties.

2.2.2 Machine Learning

The bestdemonstration of intelligence is for a machine to have automatic learning ability and even experimental knowledge accumulation. Especially important is the reasoning identification ability aided by professional knowledge. The main tasks of m achine learning in land cover classification is to select feature samples and complete supervised classification according to the knowledge achieved by Tupu, which is one of the most critical steps. The fundamental basis of both sample selection and classification lies in object features, which has been very sparse in the field of cognition. The main challenges are as follows: The applicable scope of different types and characteristics scales is limited. Regarding the unique characteristics of object relations, for e xample, if the focus is on the characteristics of j between object A and B, the focus may be more effective if also placed on the characteristics of k between object A and C. So the technology of distance metric learning and decision trees is employed to solve problems of accuracy and efficiency because the characteristic matrix $\boldsymbol{p}$ with $n \times 3$ needs to focus on $j+k$ features in practice. Many different "world problems" are couple-mapped to object feature space, using distance metric learning to find a suitable metric understanding of the current view through relearning, solving the unified standard problem in distinguishing different object features (Xing, 2003; Weinberger, 2010). The samples s elected by automatic selection on this basis have high typicality and balance the difference between various and same kinds to make samples more suitable for classification requirements and yielding higher accuracy. The decision tree algorithm is a simple and efficient classification algorithm, especially the C5.0 combined with the boosting and bagging technology and the random forest algorithm, which is suitable for large-scale classification requirements (Quinlan, 1996; Breiman, 2001). In the object-o riented process of automatic classification, the traditional classifier cannot balance efficiency with accuracy of classification b ecause of the great growth in the numbers of samples and f eatures. The advantage of using a decision tree in these cases is obvious, so many land cover classification projects do that.

2.2.3 The self-adaptive iteration

The establishment of a self-adaptive iterated circulated mechanism is an effective measure to improve precision. For a rtificial interpretation of land cover information, the general principle is to go from easy to complex, and from familiar to strange, which is the iterative information reasoning process in essence. The extraction of remote sensing data requires the use of iterative circulation. For example, the calculation of complex relations in object feature space needs the support of referent features (Wang, 2011) and the local adjustment model needs the basis of the whole domains (Luo, 2009b; Qiao, 2012). Land cover information can be improved iteratively by following several guidelines. Firstly, accessing the previous land cover result can improve the segmentation effect and contribute to the confirmation of the element scale toachievea more accurate object element. Then, the partially known features can utilize g eoscientific knowledge to calculate the spatial relationship f eatures, enriching the feature space of an object. Next, the distribution of the sample space can be improved globally with the support of the whole distribution of the object feature, making the feature sample more typical. Finally, the reference of a previous land cover classification result can also contribute to the c onfirmation of the feature classes, thus improving precision. In addition, the establishment of iterative termination criteria is also an important part of the iteration mechanism. In this paper, only part of the sample has been selected generally to make an accuracy assessment due to the huge numbers in the sample. The iteration will be terminated only when the level of precision meets the default requirement or the precision of the iterative classification is difficult to improve upon.

3 LAND COVER AUTOMATIC CLASSFICATION

3.1 Study area and experimental data

To verify the actual effect of remotely-sensed Tupu-cognition and automatic interpretation, the cities of Dong Guan, Sheng Zhen, and Hong Kong in the Pearl River Delta were s elected as test areas. The main test data are from three-view A dvanced Land Observing Satellite (ALOS) images of the same track in the cover test zone. Secondary data includes survey data of local land use, the generalized digital environment model (GDEM) altitude data (30 m), the industry standard architecture (ISA) impervious index, the spectral data of typical object features in the test area, and so on. All data was corrected by g eometry and radiation and registration in the unified management of the geographic information system platform. F ig. 3 shows land use data of the Advanced Land Observing S atellite (ALOS) image superposition.

3.2 Experimental Method

According to the land use automatic classification process, a land cover classification application system has been developed with the following specific functional steps and algorithm.

(1) Each image employsa mean shift algorithm for multiscale segmentation. The result is unified into a Geographic Information Systems (GIS) database in vector polygon form, each of which will participate in the subsequent operation as an independent primitive object.

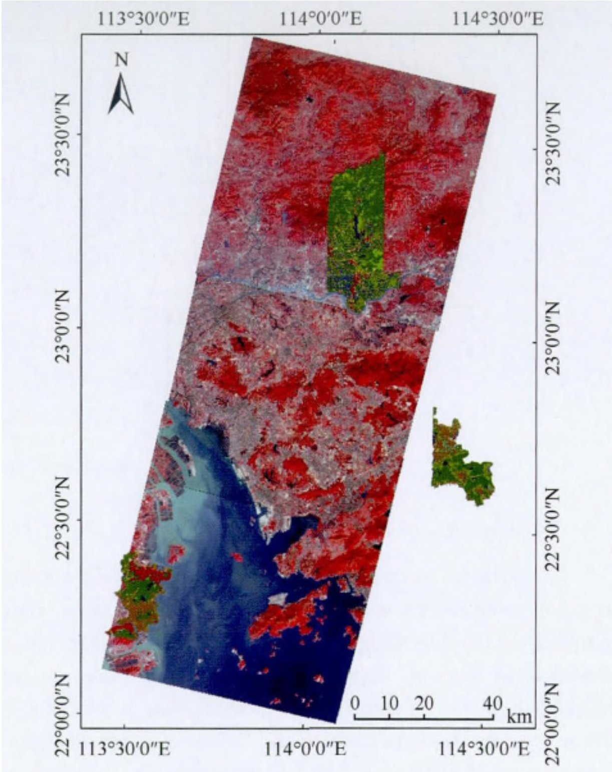

Fig. 3 Data from the study area

(2) The characteristics of each primitive objectis calculated and stored in a database according to its vector attribute form. The specific characteristics are shown in Table 1, in which the common characteristics of texture feature are calculated by just one band, such as energy, entropy, contrast, and so on. The space feature calculated by classification result is employed only in the iterative process.

Table 1 Feature parts used in classification

Feature name	Feature type	Calculated object	Amount
Average of spectrum	Spectrum	ALOS image	4
Standard deviation of spectrum	Spectrum	ALOS image	4
Relative elevation	Topography	GDEM	1
Slope	Topography	GDEM	1
Hill shade	Topography	GDEM	1
Aspect	Topography	GDEM	1
Shape index	Space	Polygon	1
Length-width ratio	Space	Polygon	1
Area	Space	Polygon	1
GLCM texture	Space	ALOS image	6
MNDWI	Spectrum	ALOS image	1
NDVI	Spectrum	ALOS image	1
Impervious index	Spectrum	ISA data	1
Distance from mountain	Space	Classification result	1
Distance from city	Space	Classification result	1
Distance from sea	Space	Classification result	1

(3) Primitive features are analyzed and samples selected a utomatically. First, supervised learning is employed to study the distance matrix combined with the land use survey data in order to improve the similarity between the similar primitives and to reduce the similarity between different primitives. The similarity of unknown primitives by this study's transformation matrix are then compared and preliminary samples selected according to the distribution requirements. At the same time samples are combined excluding abnormal spectral characteristics in the feature spectral data and index feature(there are possible errors existing in land use data). Next, the type of land use is converted to the type of land cover to form a complete sample. The main class of land cover is the first-order class, including woodland, grassland, building site(city), water, agricultural land (farmland), unused land (bare land), etc.

(4) Because the areas studied in this paper are relatively centralized, samples of multi view images have been adopted to train the model in a centralized way. The samples selected are trained by collecting three-view images with the C5.0 decision tree algorithm and then boosting to train the single model merged with many decision trees. Each image view is then classified by this model to achieve the preliminary results of classification.

(5) The classification results of land cover and land-use data are then analyzed, and the possibly mismatched areas in the data will be excluded. Then in the second iteration, the feature and sample are adjusted twice by the modified land-use data. At the same time, the relationship of the spatial distance and the other features are calculated on the basis of the former classification results and the decision tree is retrained to carry out the new classification. Meanwhile, to determine if the iterative terminal condition is satisfied, the iterative classification will continued if the condition is not satisfied until the complete classification result is obtained.

3.3 Results and analysis

Fig. 4 shows the classification result. Note that the second scene covers the first and third scene since main area is the s econd one. From a visual effect, some classes, such as city, water, woodland, farmland, and so on, are basically in line with the image with respect to their wide distribution. In the rural residential area sit is hard to distinguish the images. These can be displayed clearly for the purposes of presenting the information in the figure. The accuracy of the farmland, grassland, and bare land are difficult to confirm relatively. To validate the precision of classification results quantitatively, test samples are selected randomly by uniform block in the whole region of the study area. However, the region with field survey data will no longer employ random sampling and another random sampling block area is added by artificial interpretation with the same high-resolution phase data, balancing the typicality and randomness as a whole. To take into account the requirements of object-oriented classification and precision in the per-pixel statistics, the precision testing methods are that the number of final s tatistical samples is 561 and each sample corresponds to ahomogenous pixel area of 3 × 3 in the image. The corresponding sample area with an accuracy of 7/9 or more is counted as a c orrect classification, and is otherwise counted as a wrong classification when evaluating accuracy. From the viewpoint of application, the final result should be a unified land cover classification figure, so multi view images are counted in the same level and o verlapping areas are in the logic operation "and". Namely only when both are c orrect is the judgment made that it is correct, o therwise the judgment is an incorrect class of one layer or the class of intersection. The final classification confusion matrix is i llustrated in Table 2.

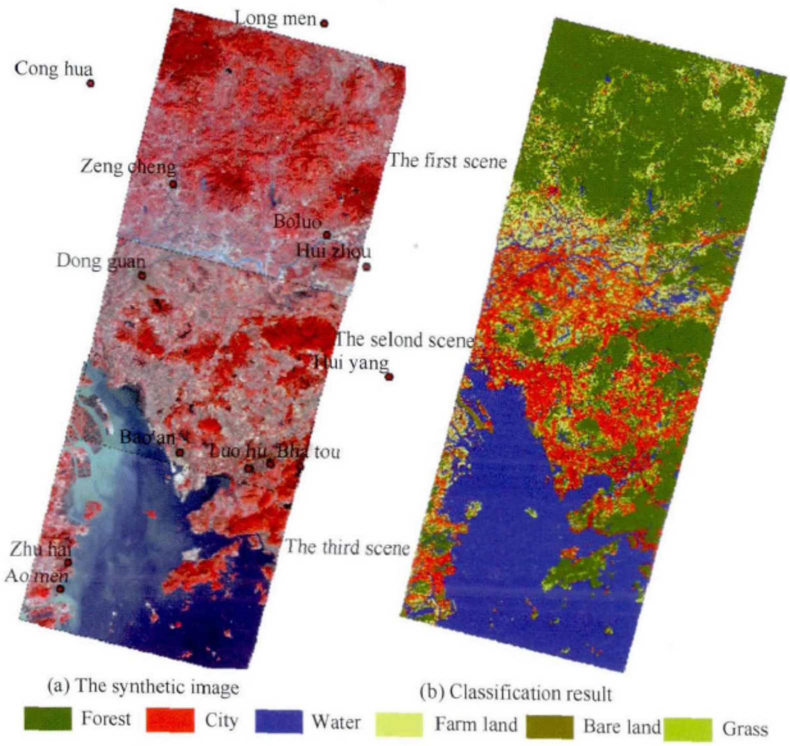

Fig. 4 Classification result

Table 2 Classification confusion matrix

	Forestland	City	Water	Farmland	Bare land	Grassland	User precision/%
Forestland	172	0	0	2	0	1	98.3
City	0	103	0	0	2	0	98.1
Water	3	3	97	0	0	0	94.2
Farmland	14	2	0	59	4	17	61.5
Bare Land	0	7	1	3	26	2	66.7
Grassland	1	4	0	1	6	31	72.1
Producer precision/%	90.5	86.6	99.0	90.8	68.4	60.8	—

The statistical accuracy of the whole classification is about 87.0% with a 0.836 kappa coefficient, in which the accuracy of forestland, city, water, and farmland is relatively high while bare land and grassland is relatively low due to their lesser quantity. The explanation lies in the data and the design of classification system. In the 10 m resolution multispectral images, the artificial interpretation standard of farmland, forestland, and grassland is mostly by inference, such as the shape of the plot, the space relationship with the city, the ups and downs of terrain, etc. This also demonstrates that further improvements are required in our method, with respect to feature extraction, iterative circulation, and other steps.

From the precision statistics process, overlapping regions belong respectively to a two-view image with a mismatch of many primitive edges, inconsistent classification, and so on. This causes the low accuracy of the classifications. The statistical r esultson the accuracy of all the three-view images according to o-verlapping regionare shown in Table 3.

Table 3 Comparison of each region on classification accuracy

Region	Sample number	Correct number	Overall accuracy/%	Kappa coefficient
1 no-overlapping	177	161	91.0	0.883
1,2 overlapping	59	46	78.0	0.741
2 overlapping	107	97	90.7	0.878
2、3 overlapping	72	45	62.5	0.577
3 overlapping	146	139	95.2	0.938

It is clearthat the classification accuracy of the overlapping regions is relatively low. The statistical result of single accuracy for three-view images is illustrated in Table 4 where the logical operation of "and" is cancelled (without consideration of the o verlapping areas in the image).

Table 4 Comparison of each image on classification accuracy

Number of view	Sample number	Correct number	Whole accuracy/%	Kappa coefficient
1	236	213	90.3	0.875
2	238	207	87.0	0.843
3	218	200	91.7	0.889

The classification results for the single view image achieves a higher level of accuracy not only due to the effect of the single algorithm but also due to the iterative calculation results in the whole processing system. To address the problem of the overlapping area, the active fusion method will be employed to improve the effect later in the process. That is, we will first fuse part of two-view image in the overlapping area then do the segmentation and classification, which will reduce the complexity of the c omputation and also maintain relatively stable precision.

4 CONCLUSION AND PROSPECT

The goal of automatic and accurate extraction of massive a mounts of remotely-sensed data, a process involving remotely-sensed Tupu cognition which is similar to the "Perceive-Identify-Confirm" process, is presented in this paper. A geological informatics Tupu methodology is used, with reference to the cognitive processes of the brain, to identify the features r emotely-sensed data. Many algorithm steps, including data a ssimilation, multi-scale segmentation, analysis of features, and supervised learning are utilized in the framework of a geographic information system. In addition, some critical technologies are i ntroduced, including the management of prior knowledge, intelligent matching learning, and self-adaptive iteration. The application of automatic interpretation using remotely-sensed information is used as an example, specifically detailing remotely-sensed Tupu analysis and its implementation algorithm. Lastly automatic land cover classification experiments with three-view ALOS i mages of the Guangdong area were carried out by the above technologies and achieved better effect. The contribution of this paper may be summarized in the following two points:

(1) The remote sensing Tupu cognitive method is presented to attempt to cognize remotely-sensed images automatically by machine, making a start toward the goal of the automated interpretation of massive amounts of remotely-sensed data.

(2) An automatic classification algorithm is developed with respect to multispectral remote sensing data and each of the main technical points of Tupu recognition is verified with the expected effect.

With the rapid development of machine learning technology and deep analysis for remote sensing, automatic interpretation of images can nowbe realized. Many deficiencies still exist in the cognitive process and algorithm application. Currently, the f ollowing points deserve further attention and improvement in subsequent theory, method, and applied research.

First, although the utilization of the GIS framework is c onvenient for the united storage and management of multisource data based on geographic attributes, it is still not to be satisfied with a number of outstanding requiirements. Traditional relational database have difficulty managing massive amounts of sparsely distributed time-space correlation data. In addition, from the data model, the extraction and expression analysis of Tupu features generally employ the vector format, while remote sensing image analysis often employs a raster format. Meanwhile, both these traditional formats have difficulty satisfying the requirements of efficiency and effectiveness. Therefore, serious consideration should be given to whether or not the two formats can be fused by an image map format.

Second, the complex imagery process of remotely-sensed data and special geological knowledge have not yet realized their full potential, with a great gap between data and information. The cognitive method of remote sensing Tupu presented in this paper follows the model of human understanding of remote sensing data. More testing data should be collected to achieve deeper levels of information other than visual interpretation to find deeper levels of geoscience rules from simulation, inversion, and computer research, to realize the next level in cognition.

Third, land coverinformation is the direct reflection of surface phenomena, while in most cases, land use information d irectly relates to the requirements of production and life. So with respect to application, the cognitive method of remote sensing Tupu needs to further combine knowledge from a variety of disciplines and extract greater amounts of information at more levels to satisfy actual application requirements. Additionally, with respect to the experiment, how to objectively evaluate classified results to correspond with both the requirements of the a pplication process while also being appropriate to each particular method must continue to be explored.

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遥感信息图谱支持的土地覆盖自动分类

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摘　要: 遥感数据的海量堆积与应用信息的匮乏日益凸显信息认知提取的重要性,在地学信息图谱方法论的指导下,同时参考视觉认知流程,提出了遥感信息图谱认知方法用于遥感数据的自动解译。在地理信息系统的统一框架下逐步挖掘多源遥感数据的"图"、"谱"特征并进行图谱耦合分析,通过多尺度分割、特征分析、监督学习等关键步骤完成"察觉—分辨—确认"的地学认知流程,初步满足自动化和智能化应用需求。在土地覆盖信息自动解译应用中建立了基于"图谱"先验知识的管理与运用机制以实现自动化,采用机器学习算法提升智能化程度,并以自适应迭代控制模型使结果精度向最优逼近。选取了珠江三角洲的试验区域进行了基于 ALOS 多光谱影像的土地覆盖自动分类,结果符合预期,说明了本文方法的可行性。

关键词: 图谱认知,自动解译,土地覆盖,自动分类

中图分类号: TP75　　文献标志码: A

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1　引　言

随着遥感影像时空分辨率的提高,数字通讯与互联网络的挑战,遥感信息流程正在逐步被定量化集成技术所替代。但全数字化和高度自动化的遥感自动分类—制图工艺流程,尚未形成规模生产,因而至今缺乏实时(或准实时)处理海量数据和多时相数据的能力,远不能满足全球变化与区域可持续发展研究的需要,也还没有充分发挥遥感数据快速、大面积覆盖的优势(陈述彭和周成虎,1997; Quartulli 和 Olaizola,2013)。陈述彭先生早在 20 世纪 90 年代就提出地学信息图谱的理念,提出要从海量数据中反演出表述景观现实的征兆图,遥感因其独特的对地观测优势是这些数据的主要来源,因此骆剑承等提出了遥感信息图谱认知与计算的理论,从"像元级"和"对象级"两个层次阐述了遥感信息图谱计算平台的设计(陈述彭和陈星,2004; 骆剑承,2009a)。田永中和岳天祥(2003)认为在遥感影像的自动解译中,引入图谱,可以提高分类精度,发现新的知识。这些问题和研究基础促使我们开始考虑如何从海量遥感数据中自动化、智能化地提取有效信息,发现地学规律,指导社会实践,其中首先需要解决的就是数据向信息的转化(Datcu 和 Seidel,2005)。遥感的主要对象是地球表层,因此土地覆盖信息是遥感数据反映的主要信息,也是各类应用基本所需求的信息,在海量遥感数据的支持下,很多以计算机为主、人工辅助的方法进行大范围土地覆盖信息提取的项目得以开展(Homer 等,2004; Friedl 等,2010),然而目前还未能实现完全自动化(主要受样本选择等步骤的制约),提取精度也有待提高,如 Huth 等(2012)提出的 TWOPAC 自动分类流程仍需要使用者选取分类及验证样本,Hu 和 Wang(2013)采用决策树完成的土地利用分类精度仍然较低。因此自动分类方法与精确模型的应用

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需求还有一定距离，难以大范围推广应用。

从人工智能的很多研究来看，计算机模拟人的认知过程是最终解决数据—信息严重不对称的可能途径，认知心理学、视觉神经生理学以及计算机视觉认知模型在近年来也有了长足发展，如由计算机运算方式引申而来的信息加工学说成为主流的认知心理研究取向（Best，2000；彭聃龄，2004），大脑视觉皮层各单元的功能与视觉信息分层逐步处理过程也随着功能性磁共振成像（fMRI）等技术的引入而进一步得以确认（Wandell 等，2007），基于视觉信号分层处理的深度学习理论也被很多学者所认可（Hinton 等，2006；Bengio，2009），这些学科理论的逐渐完备和实践开展也促进了遥感信息图谱认知方法的形成和发展。

在上述研究的基础上，根据从遥感数据中自动提取地理空间信息的实际需求以及一般流程发展了遥感信息图谱认知方法。以视觉认知理解流程为参考，以地学征兆图谱为目标，试图实现自动化、智能化的遥感信息自动解译与提取，为遥感数据的充分利用提供技术支持。以土地覆盖信息为例根据遥感信息图谱认知方法和实际数据条件及应用需求对传统分类算法进行了改造，在多源数据的支持下实现了对多光谱遥感影像的自动分类并快速提取大规模土地覆盖信息，实验取得了良好效果。

2 遥感信息图谱认知

2.1 地学信息图谱指导下的图谱认知

地学信息图谱是对地理空间系统及其各要素和现象进行“空间格局”和“时间过程”的复合特征进行分析，进而实现智能化认知的地球信息科学方法论（叶庆华 等，2004）。地学信息图谱在工作流程上可以根据功能分为征兆图谱、诊断图谱和实施图谱（陈述彭 等，2000），其中与数据直接相关的征兆图谱是信息提取模型对有关数据的运行结果，可为本文进一步研究提供线索和依据（张百平 等，2009），也是遥感信息图谱认知的主要关注点。

遥感作为地表信息直接获取的有效手段，自然成为信息提取的基本对象，而遥感信息图谱认知方法就试图通过模拟人脑“察觉—分辨—确认”的视觉认知过程建立类似的信息提取机制，从而实现自动化、智能化地生产地学征兆图，这其中的关键是对遥感影像进行图谱耦合分析。如图 1 所示，首先各类数据在地理信息系统的框架下以地理属性为依据用图形的形式管理、展现、利用，这个过程的主要任务就是多源数据的获取与管理；然后在图谱认知的第一个阶段需要使机器“察觉”到影像中的地物，这一方面需要各类先验知识的辅助，另一方面还需要对实际影像进行多尺度分割，初步确定地物空间属性（地理分布、空间尺度等）；接着在图谱认知的第二个阶段需要使机器主动“分辨”具体地物，在此不但要分析地物的具体特征（光谱、形状、地形、时间、相互依赖等），而且要结合影像内容和先验知识有针对地进行主动学习，积累地物判别经验；接着在图谱认知的最后阶段需要最终“确认”影像中的地物信息，亦即根据认知结果给影像内容赋予语义，同时以图的形式向地理信息系统进行反馈，一方面可以通过迭代方式重新检查以改进自身的精度，另一方面也可以作为先验知识存储以备后用，这个过程的主要任务是生成地学征兆图谱；至此已经可以根据应用需求将征兆图谱输入各种时空分析模型进一步研究，最终生成地学诊断图谱进而指导实施。

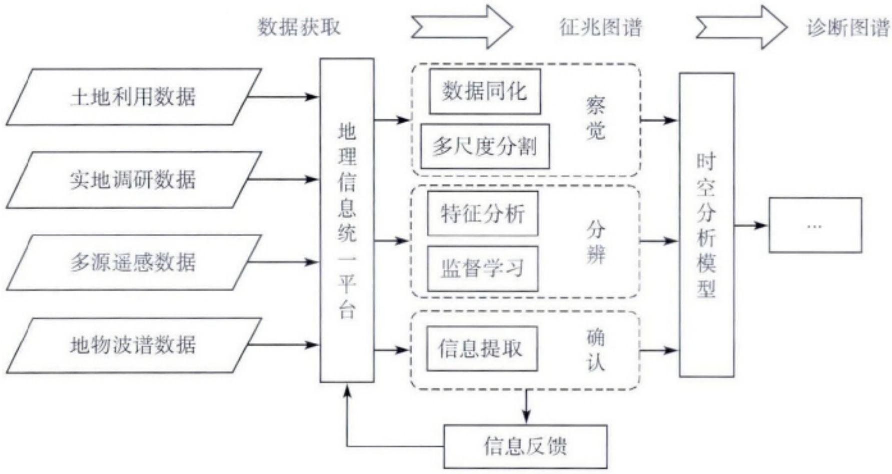

图 1 遥感信息图谱认知流程

图谱耦合分析贯穿遥感信息图谱认知的整个过程,主要以两种形式完成:一是"图式"分析,这种分析将地物与其所处环境相联系,在不同参考系下从不同尺度、不同角度全方位地加以考察,有助于从宏观上把握地物的分布规律;二是"谱相"分析,这种分析对地物进行深入剖析,不仅在过去到现在的演变上,而且在不同光学波段的反射上,有助于从微观上把握地物的变化规律。

在认知流程的"察觉"阶段,认知更多的依赖"图"的知识并且作用在"图"的层次,首先不同数据基于地理属性而同化,即使是各类统计数据最终也须地图化以输入;其次多尺度分割可以看成是一种基元提取的图式分析,基元作为认知单元与传统的像元对应,从遥感处理的角度考虑基元可以高效处理空间上连续的同质像元组,从认知的角度考虑基元可以承载更多的地物特征与知识,最终以地理属性为参考进一步由基元组成未知地物图(基元图)。然后在"分辨"阶段,认知更多的依赖"图—谱"的知识耦合,首先经过对基元"图—谱"特征的有效提取与表达分析进一步形成了特征基元,它与地物目标的联系更加紧密,可以作为后续监督学习、分类判别的基本单元;其次监督学习中的先验知识也以"图"、"谱"的形式应用,如地物波谱、形状、纹理等,而且监督分类的过程主要就是对特征的进一步处理,而样本不过是各类地物特征的承载体。最后在"确认"阶段,认知结果同样以"图"的形式表现并储存,在地理信息系统下还可以进行各种矢量操作处理。

在地理信息系统框架的约束下,数据以矢量或栅格形式独立存在,有限的分析手段制约了我们对信息图谱的提取和利用,而且其中的主要数据源遥感影像的"图谱"本质也要求我们尽量采用图谱化分析,因此耦合"图-谱"分析,模拟认图知谱、译谱识图是整个认知过程的关键,从纵向上打通"像元-基元-特征-地物"的递进模型,在横向上解决图谱特征的耦合问题,充分发挥先验知识的作用,挖掘遥感影像的潜力,实现遥感信息的自动解译。

2.2 遥感信息自动解译应用方法

从实际应用考虑遥感信息自动解译至少应满足两方面的应用需求,一是自动化的信息提取,这也是针对海量遥感数据实时(或准实时)应用的需求,从机器学习的角度来看,要想使机器能够自动实现应用目标有两个层次的衡量标准:自适应和自学习,前者使机器能在无人工干预下完成特定任务,后者使机器能主动发现知识提取更符合需求的信息;二是智能化的信息提取,这也是遥感信息得以真正应用于相关行业的基础,从遥感应用的角度来看,要想使遥感影像中自动提取的信息为人所用有两个重要标准:高精度和高容错,前者是单个应用案例中使遥感信息可信的标准,后者是业务化运行中使遥感信息稳定可用的标准(Baraldi 和 Boschetti,2012;张良培和黄昕,2009)。

根据遥感信息自动解译技术要点和土地覆盖分类的实际需求,本文设计了土地覆盖信息认知的一般流程,初步对认知方法进行了实际应用拓展。如图2所示,首先,地理信息系统作为统一框架整合各种数据和信息,其中主要包括土地利用数据、地形数据、外业实地调查数据、典型地物波谱数据以及最主要的多源遥感数据,这些数据统一到相同地理参考系下,确保每一个像素对应的辅助数据与信息均能被及时检索到;然后使用多尺度分割算法提取合适尺度的基元并计算各类特征(光谱、形状、纹理、地形、环境条件、各类指数等),计算过程中可能会使用各种辅助数据,这是图识谱的"察觉"阶段;然后在自动样本选择过程中主要是对各类知识的应用,一方面对基元特征进行分析,特别是将光谱特征与典型地物的波谱特征进行匹配,另一方面分析基元对应的前期土地利用类型,建立可能的变化与联系;接着在大量样本的辅助下对所有基元进行监督分类,此时主要关注分类模型的性能以及模型判别经验的积累,使算法适合于大面积应用,这是译谱识图的"分辨"阶段;最后在GIS框架下进行迭代分类,达到数据与信息的进一步吻合,至此完成最终"确认"。自动解译得到土地覆盖信息是遥感信息图谱认知的基本应用目标,后续的算法包括LUCC分析、时空分析等暂未考虑。

图1流程的关键在于GIS下类似自循环的信息流通,其中主要的难点如下:

2.2.1 先验知识管理

自动化的基础是对研究对象有一定了解,即先验知识的存在,用于辅助土地覆盖分类的先验知识可以分为两类:一类是"图"的知识,以前期土地利用数据为典型代表,这类数据从空间分布上指出某个区域的可能地物,告诉机器"哪里有什么"的知识,这种基于存储的知识一般更适合机器进行处理;另一类是"谱"的知识,以地物波谱库数据、植被生长规律为典型代表,这类数据从光谱、时间序列

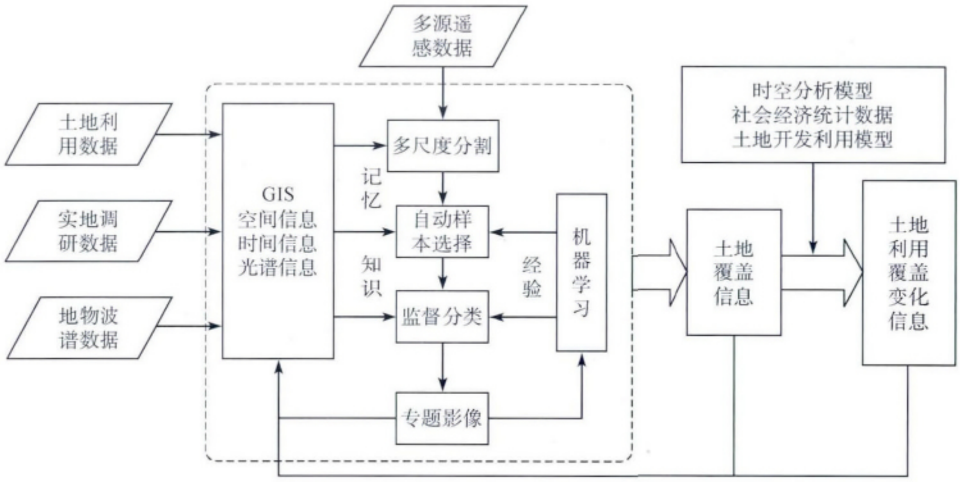

图2 土地覆盖信息认知流程

上指出某种地物在影像上的可能表现,告诉机器"什么是怎样"的知识,这种基于计算的知识目前机器处理的效果远不如人脑。如何使机器结合并利用好这两类先验知识不但关系到能否自动化实现土地覆盖分类,而且与最终分类结果的精度也密切相关,上述前一种方法是了解特定地理位置在特定时刻分布何种地物及其变化规律,如城市化扩张过程中荒地、农田向城镇的转变等,这种方法着眼于地物在时空变化上的客观连续性,对影像的空间分辨率有一定要求; 后一种方法是了解各种地物的本质特征及其在影像上表现的特征,如水体在近红外波段常表现为强吸收,而植被常表现为高反射,水稻在生长过程中叶面积指数随时相的变化等,这种方法着眼于局部区域内地物特征的一致性,对影像的光谱分辨率有一定要求。更好地管理这些先验知识是采用 GIS 统一框架的初衷,以地理属性为基本要素对所有知识进行存储、查询、更新是目前较可行的办法。

2.2.2 机器学习

智能化的最好表现就是使机器具备自动学习甚至经验积累能力,特别是在领域专业知识辅助下的推理识别能力,在土地覆盖分类中机器学习的主要任务就是根据"图"、"谱"知识自动选择地物样本并完成监督分类,可以说是其中最关键的步骤。无论是样本选择还是分类,其根本依据在于地物特征,而地物特征从认知的角度考虑具有极大的稀疏性,主要表现在: 不同类型的特征,不同尺度的特征,特有的地物关系特征的适用范围均是有限的,如 A、B 地物间需关注某 j 类特征,而 A、C 地物间则只需关注某 k 类特征。于是在 $n \times 3$ 的特征矩阵 P 中实际仅需关注 $j+k$ 个特征($j, k \ll n$,n 为总特征数),因此我们主要采用了距离度量学习和决策树等技术解决其中的精度与效率问题。地物特征空间由多个不同"问题世界"的耦合映射,距离度量学习可以在这个复杂空间重新学习适合当前视角的度量方法,从而解决了我们区分不同地物的统一标准问题(Xing 等,2003; Weinberger 等,2010),在此基础上自动选择得到的样本具有更高的典型性,兼顾各种类别间的区别与同种类别内的区别,从而使样本更符合分类需求,提高监督分类的精度。决策树算法是一类简单高效的分类算法,特别是分别结合了 boosting 和 bagging 技术的 C5.0 和随机森林算法已经达到较高精度,比较适合大规模分类需求(Quinlan,1996; Breiman,2001),在面向对象的自动分类流程中,样本数量与特征数量都大大增加,传统的分类器难以兼顾分类效率与精度,而决策树在这方面的优势比较明显,因此许多全球、区域尺度的土地覆盖分类项目也采用此方法。

2.2.3 自适应迭代

自适应迭代循环机制的建立是提高精度的有效手段,对于土地覆盖信息的人工判读,一般的原则是从简单到复杂,从熟悉到陌生,这本质上是一种信息的迭代推理过程,而遥感信息提取中也确实需要迭代循环的参与,如复杂的地物空间关系计算需要有参考地物作为支持(王卫红,2011),局部的调整模型需要全域的计算作为基础(骆剑承 等,2009b; Qiao 等,2012)。土地覆盖信息可以通过以下几方面迭代改进: 首先在前期覆盖结果的支持下

可以改进分割效果,有助于基元尺度的确定,从而得到更准确的地物基元;其次已知部分地物后可以更多的利用地学知识计算空间关系特征,从而丰富地物基元特征空间;再次在整体地物分布的支持下还可以从全局上改善样本的空间分布,使自动选择的地物样本更具有典型性;最后通过参考前期覆盖分类结果也有助于确认地物类别,从而提高最终精度。此外,迭代终止准则的建立也是迭代机制的重要内容,在本文的方法体系下由于自动选择的样本数量庞大,一般可以选取部分用于精度评价,只有当精度符合预设要求或者迭代分类的精度难以再继续提高时才终止迭代(此时上述改进精度的方法已无法继续发挥作用)。

3 土地覆盖自动分类

3.1 研究区及实验数据

为验证遥感信息图谱认知及自动解译方法的实际效果,本文选取了珠江三角洲的东莞、深圳、香港等城市群所在区域为实验区域,以覆盖实验区的同一轨3景ALOS影像作为主要实验数据,其他的辅助数据包括部分区域的土地利用调查数据、GDEM高程数据(30 m)、ISA不透水指数、试验区典型地物波谱数据等,这些数据经过几何、辐射校正并相互配准后在地理信息系统平台下统一管理。图3为ALOS影像叠加土地利用数据。

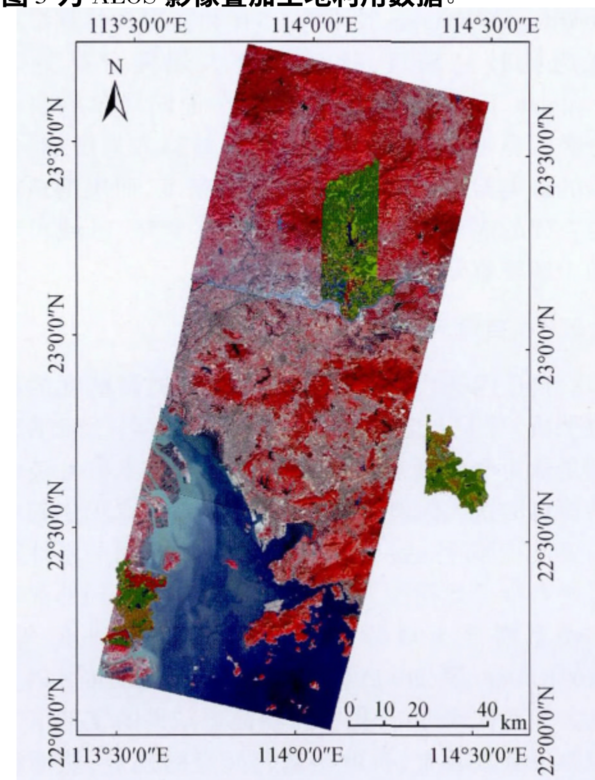

图3 研究区数据

3.2 实验方法

按照土地覆盖自动分类的流程本文开发了土地覆盖分类应用系统,具体功能步骤及算法如下:

(1)采用均值漂移算法分别对每景影像进行多尺度分割,分割结果以矢量多边形(Polygon)统一到GIS系统数据库内,根据尺度不同多边形数量变化较大,每个Polygon作为独立基元对象参与后续运算。

(2)计算每个基元的特征并以矢量属性的形式存入数据库,具体特征如表1所示,其中纹理特征仅按照一个波段计算能量、熵、对比度等常用特征;根据分类结果计算的空间特征仅在迭代过程使用。

表1 部分分类特征

特征名称	特征类型	计算对象	数量
光谱平均值	光谱	ALOS影像	4
光谱标准差	光谱	ALOS影像	4
相对高程	地形	GDEM	1
坡度	地形	GDEM	1
山体阴影	地形	GDEM	1
坡向	地形	GDEM	1
形状指数	空间	Polygon	1
长宽比	空间	Polygon	1
面积	空间	Polygon	1
GLCM纹理	空间	ALOS影像	6
水体指数	光谱	ALOS影像	1
植被指数	光谱	ALOS影像	1
不透水指数	光谱	ISA数据	1
与山体距离	空间	分类结果	1
与城市距离	空间	分类结果	1
与海岸距离	空间	分类结果	1

(3)分析基元特征并自动选择样本,首先结合土地利用调查数据监督学习距离度量,以达到同类基元间相似度提高、非同类基元相似度降低的学习目标。根据学习得到的变换矩阵比较未知基元间相似性,根据分布要求初步筛选样本,同时结合地物波谱数据与指数特征剔除光谱特征异常的样本(土地利用数据可能存在错误);然后将土地利用类型转化为土地覆盖类型,形成完整样本。土地覆盖

类型以一级类为主，包括林地、草地、建筑用地(城市) 、水域、农业用地(耕地) 、未利用地(裸地) 等。

(4) 由于本文研究区域相对集中，为保证分类一致性采用多景影像的样本集中训练一个模型，即集合 3 景影像中分别选择得到的样本训练 C5.0 决策树算法，采用 Boosting 训练多棵决策树融合成单一模型，然后以此模型对各景影像分别分类，得到所有影像的初步分类结果。

(5) 将土地覆盖分类结果与土地利用数据匹配，剔除土地利用数据中可能存在的不匹配区域，然后进行第 2 次迭代，根据修改的土地利用数据对特征、样本进行二次调整，同时在前期分类结果的基础上计算空间距离关系等特征，重新训练决策树并分类，同时判断是否满足迭代终止条件，未满足则继续迭代分类，直至最后得到完整的分类结果。

3.3 结果及分析

图 4 为分类结果(由于第 2 景为主要区域，显示时将其覆盖第 1 景、3 景) ，从目视效果来看，城市、水域、林地、耕地等类别由于分布较广，基本上与影像相符，由于分类图的信息展现方式，甚至能将影像中较难分辨的农村居民点清晰显示，而耕地、草地、裸地的准确程度相对难以判定。为了量化验证分类结果的精度，本文对研究区域总体上进行均匀分块随机采集测试样本，对于有外业调查数据的区域则该分块不再随机采样，其余随机采样分块区以相同时相的高分辨率数据人工判读结果补充，总体上兼顾典型性与随机性。为兼顾面向对象分类与逐像素统计精度的需求，采用如下精度验证方法: 最终统计采样数为 561 个，每个样本对应影像中 3 × 3 同质像素区域。在精度评价时结果中对应样本区域正确率大于 7 /9 时以分类正确计数，否则以分类错误计数; 从应用角度考虑最终结果应为一张统一的土地覆盖分类图，于是对多景影像统一计数，重叠区域进行逻辑“与”操作，即两者都正确时才判断为正确，否则判断为错误一层的类别(一对一错) 或两者交集类别(两者都错) 。最终的分类混淆矩阵如表 2 所示。

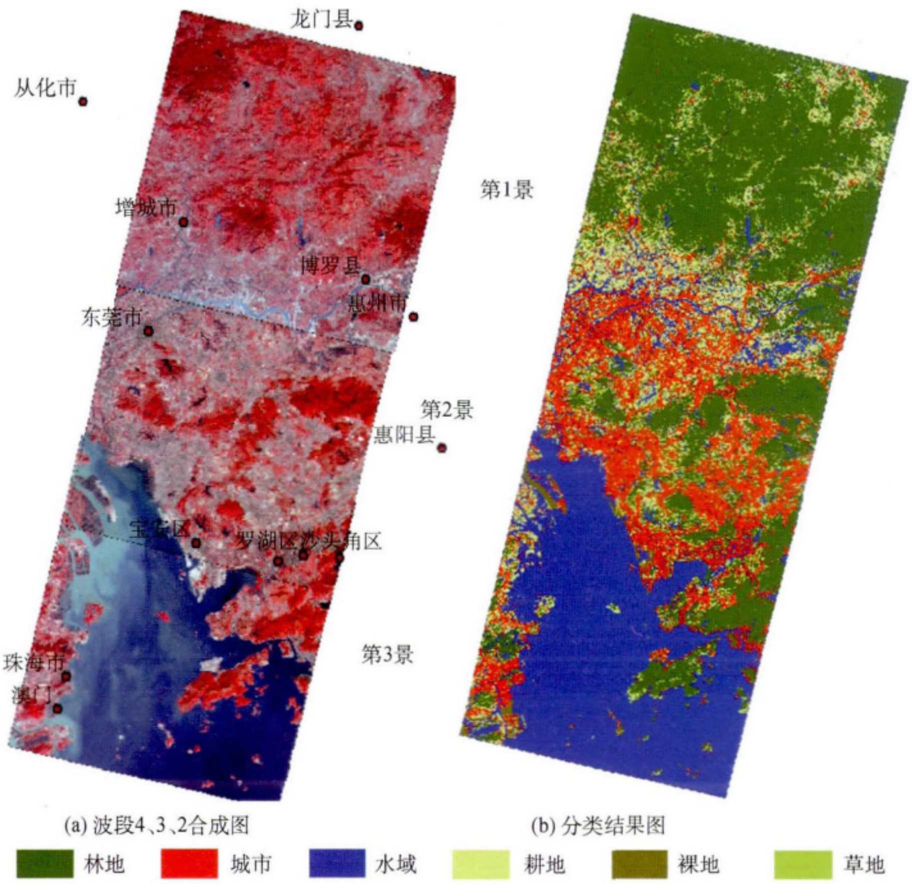

图 4 分类结果

表2 分类混淆矩阵

	林地	城市	水域	耕地	裸地	草地	用户精度/%
林地	172	0	0	2	0	1	98.3
城市	0	103	0	0	2	0	98.1
水域	3	3	97	0	0	0	94.2
耕地	14	2	0	59	4	17	61.5
裸地	0	7	1	3	26	2	66.7
草地	1	4	0	1	6	31	72.1
生产者精度/%	90.5	86.6	99.0	90.8	68.4	60.8	—

由表2可知,统计总体精度约为87.0%,Kappa系数为0.836,其中林地、城市、水域、耕地精度相对较高,而裸地与草地数量较少,精度也相对较低。这里边有数据的原因,也有分类系统设计的问题,在10 m分辨率的多光谱影像中,耕地、林地与草地的人工判读标准多是推断性的,如以地块的形状、与城市的空间关系、地形的起伏等,这也说明了本文方法在特征提取、迭代循环等环节需要进一步改进。

从精度统计过程来看,重叠区域分属两景影像,存在较多基元边缘不吻合,类别不一致等现象,导致分类精度有所降低,将3景影像按重叠区域分别统计总体精度,结果如表3所示。

表3 各区域分类精度比较

区域	样本数	正确数	总体精度/%	Kappa系数
1未重叠	177	161	91.0	0.883
1、2重叠	59	46	78.0	0.741
2未重叠	107	97	90.7	0.878
2、3重叠	72	45	62.5	0.577
3未重叠	146	139	95.2	0.938

可以明显发现重叠区域的分类精度相对较低,如果撤销精度统计中的逻辑"与"操作(即不考虑重叠区域影像),对3景影像的单独精度统计结果如表4所示。

表4 各景分类精度比较

景号	样本数	正确数	总体精度/%	Kappa系数
1	236	213	90.3	0.875
2	238	207	87.0	0.843
3	218	200	91.7	0.889

单景影像的分类结果都达到了较高的精度水平,这并不仅仅是单个算法的作用,而是整个系统流程化迭代计算的结果。针对重叠区问题后期将采用主动融合的方法加以改进,即在重叠区对两景影像部分融合然后进行分割与分类,不但能减少运算量,而且能使精度保持相对稳定。

4 结论

本文以海量遥感数据的自动精确提取为目标,在地学信息图谱方法论的指导下,参考人脑的认知过程,针对遥感数据的特点,提出了类似"察觉—分辨—确认"的遥感信息图谱认知流程。在地理信息系统的框架下实现了针对海量遥感数据的数据同化、多尺度分割、特征分析、监督学习等算法步骤,并以遥感信息自动解译的应用为例重点介绍了先验知识管理、智能机器学习、自适应迭代等关键技术,着重指出其中的遥感数据图谱化分析手段及其具体实现算法。最后基于上述技术方法进行了广东地区3景ALOS影像的土地覆盖自动分类实验,取得了较好的效果。归纳来讲本文的贡献主要在于以下两点:

(1)提出了遥感信息图谱认知方法,试图使机器自动认知遥感影像,开始向着海量遥感数据的自动化解译的目标迈进。

(2)发展了针对多光谱遥感数据的自动分类算法,对图谱认知的各技术要点进行了验证,实验也达到了预期的效果。

随着机器学习技术的快速发展以及人们对遥感过程的深入分析,我们相信影像解译的自动化并非遥不可及。当然在目前的认知流程与算法应用中存在许多不足,就目前来看,以下几点值得我们在后续理论、方法和应用研究中进一步完善:

(1)采用GIS这一框架虽然给多源数据基于地理属性统一存储管理提供了方便,但仍难以满足发展的需求,首先面对海量的时空相关且稀疏分布的数据,传统的关系数据库难以较好管理;其次从数

据模型来看,图谱特征的提取和表达分析一般在 GIS 下采用矢量格式,而遥感影像多采用栅格形式,传统的矢量化或栅格化在效率和效果上均难以满足发展需求,能否以影像地图的形式融合这两种格式也是值得深思的问题。

(2) 遥感数据复杂的成像过程、蕴涵的特殊地学知识仍未被完全认知,数据与信息之间的鸿沟难以从根本上跨越,而本文的遥感信息图谱认知方法还是跟随人类理解遥感数据的模式,然而很多深层次信息并非目视解译所能获取,因此需要采集更多实测数据,从计算机的角度模拟、反演、学习,发现更深层次的地学规律,实现认知的更上一层楼。

(3) 土地覆盖信息是地表现象的直接反映,然而多数情况下土地利用信息才是与生产生活直接相关的需求,因此从应用上来看,遥感信息图谱认知方法需要进一步与多类型知识结合,提取更丰富、更多层次的信息,满足实际应用需求。另外从实验的角度来看,如何客观评价分类结果,使其不但与应用过程中的需求相切合而且适应方法的特殊性也需要继续探索。

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