Remote sensing image classification method supported by spatial adjacency

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Abstract: The image classification is a key step for remote sensing data transforming into practical information and knowledge, which has always been the core problem in the remote sensing field. The limitations in traditional spectral classification method otherwise promotes the theory development on the spatial-spectral coupled information cognition of remote sensing, which focuses more on the spatial relationship. However, the current classification revision methods have configured the spatial forms and relationship while, going further, but there still exist some deficiencies in spatial distribution theorem about quantitative description, objects' actual distribution, and so on. Thus, the paper proposes a spatial-adjacency-supported classification revision method inclusive of reference object extraction, target object pixels searching and reference adjacent objects distinguishing which detailed steps are: (1) marking the objects out and getting their distribution rangepicking up the other objects in the range, (2) selecting them as the target object, picking out the unavailable target object in the range and selecting them as a certain objectwhich also provides a convenient and effective way for stepwise and accurate extraction of other objects subsequently. We also carried out an experiment on offshore area classification revision, and the result proved to be more accurate and reasonable.

Key words: remote sensing classification, spatial-spectral coupled information, spatial adjacency, classification revision

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1 INTRODUCTION

Classification is always an important and difficult point in the field of remote sensing, and also the key step to transfer remote sensing technology into practical application. The previous dominant classification methods which mainly depended on image spectal information have the shortages: the deficiencies of spectral confusion and limited information. With the development of high resolution remote sensing, the shortages of the methods are becoming more and more obvious. Therefore, cognition theory of spatial-spectral coupled information on remote sensing wins extensive concern and application.

Remote sensing data possesses both spatial and spectral features essentially: firstly, the image which represents spatial information, gives us the intuitive visual sensation, and generally reflects objects' spatial distribution; secondly, the spectrum which reflects objects' formation mechanism quantitatively and becomes basic quantitative feature to express objects in image. Accordingly, the cognition theory of spatial-spectral coupled information on remote sensing organically integrates meticulous radiant spectral feature and spatial distribution feature and represents the actual ground cover from different aspects true and comprehensively (Luo, *et al*, 2009b).

Spatial information such as shape and texture have been introduced in many researches which can got better results and be called the preliminary practice of spatial-spectral coupled information. However, the method only by using basic spatial information is still inadequate for the classification of high resolution on the mixed ground cover, such as city and offshore area and can not meet the request of practical application. Spatial relationship is thereby adopted by some researchers to amend the image classification results: Wu, *et al.* (2006) used distance relationship to amend the classification results of coastal zone; Zhao, *et al.* (2003) used spatial relationship to structure two bands for classification; Cai, *et al.* (2006) used polygon adjacent relationship and DEM to amend the initial classification result of wetland, grassland, farmland (Bian, *et al.*, 2009; Chen, *et al.*, 2004; Di, *et al.*, 2000; Soe, 2008). Although all kinds of methods mentioned above have partly reduced the misclassification by only using spectral data on spectral heterogeneity within the same class and the homogeneity between different classes, they could not recognize the actual geographic

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distribution of ground cover. In this paper, we propose a remote sensing image classification method on the basic of spatial adjacency and the cognition theory of spatial-spectral coupled information, which is proved accurate and effective by experiment on offshore ground cover classification.

2 CLASSIFICATION SUPPORTED BY SPATIAL ADJACENCY

2.1 Classification principle supported by spatial adjacency

The first law of geography is spatial adjacency, that is, everything is related with each other, and the closer of things in spatial distance, the stronger of their relationships (Miller, 2004; Tobler, 1970). Spatial adjacency is a concrete expression of it. As is known to all, many natural objects exist correlated, such as the adjacent relationship between beach and sea, wetland and water. Accordingly, if one object is determined, it can be the reference object to infer the other related target object. In this paper we only discuss the target and reference objects which are significantly related, searched and labeled to determine the distribution of other objects and make some revision. This is a revision on large scale based on the cognition theory of spatial-spectral coupled information, which adopted spatial adjacency to do revision based on rough classification result by using spectral information, and its flow chart is shown in Fig.1.

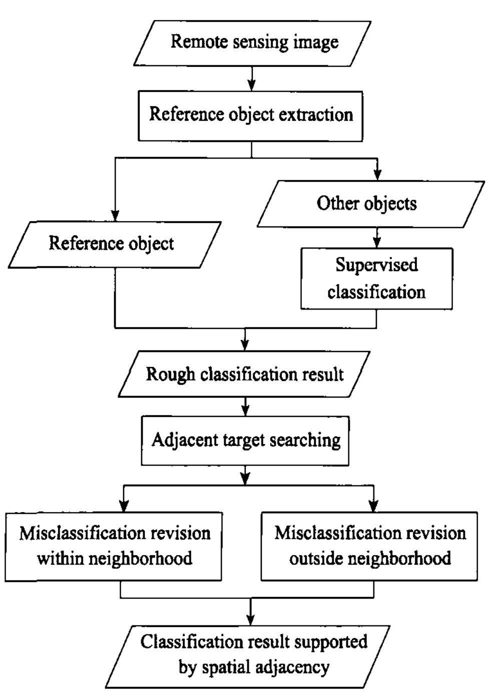

Fig. 1 Flow chart of classification supported by spatial adjacency

Firstly, this algorithm extracts reference object from the original remote sensing image to gain an image only bearing reference objects; secondly, masks the reference object to obtain the partial of image exclusive of the reference object and proceed the supervised classification on the partial image; thirdly, combines the supervised classification result and the reference object image to achieve a whole rough classification result; forthly, uses spatial adjacency to search target object to determine its distribution on the basis of rough classification; lastly, infers the other objects' distribution and make some necessary revision to obtain a more factual and accurate classification result.

2.2 High precision reference object extraction

Reference object is supposed to possess the unique spectral features, such as concentrated distribution and easy extraction, for example, water body. As the prior knowledge, its accuracy determines subsequent amendment degree, so its high precision extraction is required.

According to its features, the reference object is always extracted by means of single-band threshold, band difference/ ratio. At the meantime, index method, which is the nearly developed and widely adopted ones, is also feasible. However, only index is not enough to get object's distribution boundary precisely that we adopt a multi-level thematic information extraction model based on index to extract reference object, which adds in hierarchical classification on the basement of index, by using spatial stepwise approach to pursue reference object's distribution.

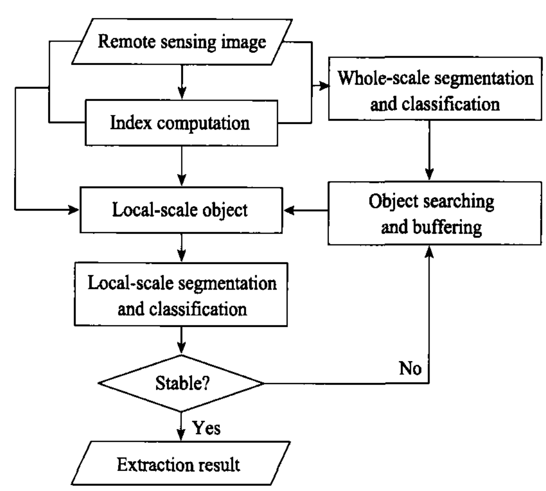

Fig. 2 High-precision extraction model of reference object

The model firstly does index computing in original image to get the quantitative enhancement of reference object on the whole scale; secondly, do segmentation in the index image to get the preliminary separation of reference object and background information, and then automatically selects samples of the two in the segmentation image, adds more image bands for the classification with classifier to get reference object extraction on whole-scale; thirdly, on the basis of whole-scale reference object extraction, searches for local-scale distribution of each reference object unit, pursue the buffering operation on them to get each reference object area for local-scale information extraction; lastly, repeats the procedure of segmentation and classification iteratively within each local area to realize the accurate approach of reference object extraction step by step. (Luo, *et al.*, 2009a).

2.3 Classification revision supported by spatial adjacency

In the part of rough classification image, each object has attribute values of, its own which is the gist for the proposed method to search, differentiate objects and realize the revision through changing the value. This method is operated on the pixel level, and the major processes are as follows.

Step 1 Reference object searching: traverse rough classification image and search image pixels of reference object by its attribute value *O*. Meanwhile remove those beyond the set threshold of size or distance if necessary to avoid noise disturbance and ensure the accuracy at the beginning.

Step 2 Reference objects refining: if necessary, pursue revision supported by adjacency on found reference object, assign attribute value *O* to the misclassification pixels which confuse with target object, and revise them into reference object to assure the adjacent relationship between the reference object and the target object.

Step 3 Target object searching and labeling: start from refined reference object, according to attribute value *T* of target object, search target object pixels which are adjacent to reference object in eight-neighborhood way, label them with *TRUE* while those are not unlabeled.

Step 4 Misclassification revision of confused objects: within the target area labeled TRUE, search the confused objects inside it, and assign attribute value *T* to them.

Step 5 Misclassification revision of target object: search unlabeled target object pixels by attribution value *T*, that is the misclassification, and assign their attribute values to real geographic objects accordingly.

3 EXPERIMENT ON OFFSHORE AREA CLASSIFICATION

3.1 Experiment on simple offshore area classification

The experiment is done at a domestic offshore area, which is a stretch of 10 km^2 areas extending 1.5 km towards inner-land and seawater, respectively. The adopted remote sensing image is a formosat-2 satellite image of this area captured in summer, with multi-spectral bands and 8 m resolution (shown in Fig.3 (a)). This area is a typical transition zone from seawater to inner-land, having some mutual and easily confused objects, such as water-land alternative zone, beach, road and building in urban area, which leads to many misclassifications using traditional spectral classification. However, spatial information represents significantly here: there are close adjacent and hierarchical relationships among objects, and confused objects have similar spectrum but different distribution, such as sea, water-land alternative zone and beach are adjacent to each other, beach only exists in offshore area. Thus, spectral classification supported by spatial adjacent, that is "spatial- spectral coupled information" classification method is quite necessary and effective here.

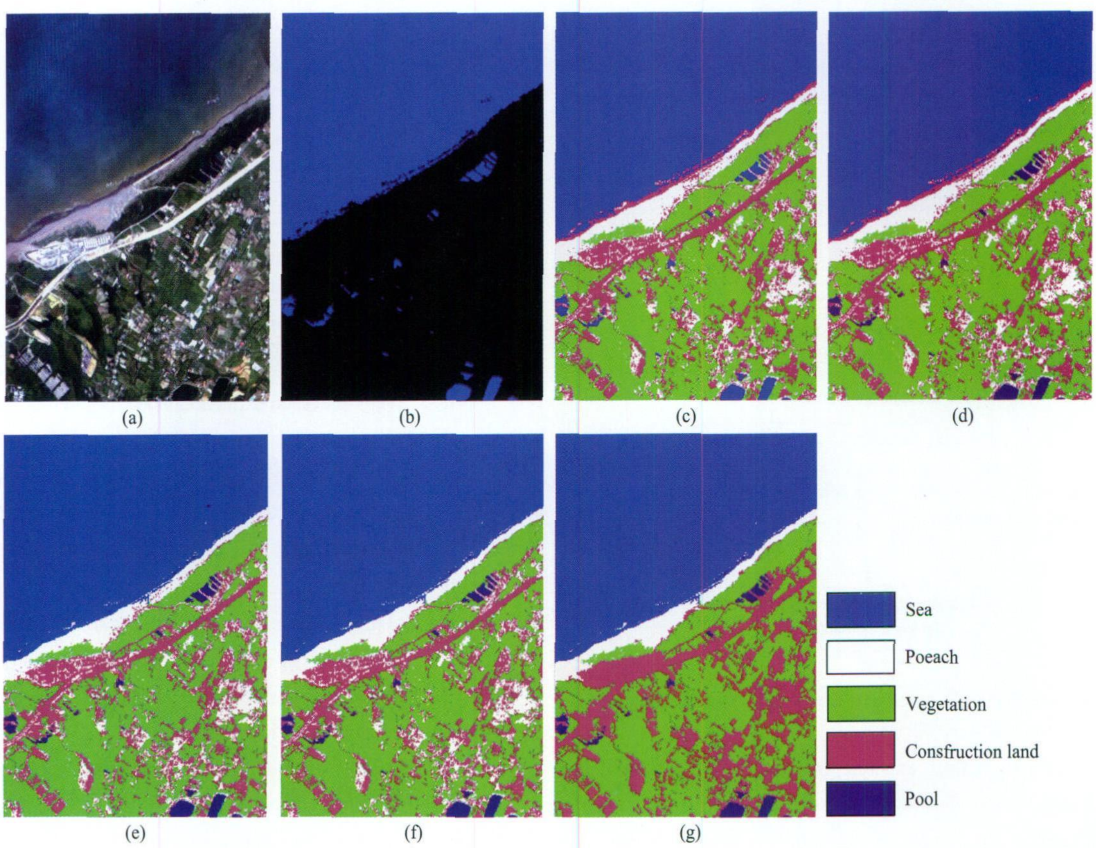

Fig. 3 Process diagram of simple offshore area classification supported by spatial adjacency

(a) Original image; (b) Water extraction; (c) Rough classification result; (d) Separation of pool from sea; (e) Revision in intertidal zone; (f) Construction land revision inside beach; (g) Beach revision inside construction land

3.1.1 Reference object extraction and Pre-classification

With the features of reference object, sea is selected as the reference object in this case, and then it should be extracted precisely. According to the high-precision thematic object extraction model mentioned above, here normalized difference water index (NDWI) (Xu, 2005) is adopted to compute water index. The equation is as follows.

$$\mathrm{NDWI} = \frac{\mathrm{GREEN} - NIR}{\mathrm{GREEN} + NIR}$$

After water has already been extracted precisely (shown in Fig.3 (b)), use it as a mask to do maximum likelihood classification for the rest of the image and get initial rough classification image (shown in Fig.3 (c)). Since the algorithm is to amend the misclassification in the whole scale, the classification system adopted here only contains water body, beach, vegetation and construction land (mainly road and building) four categories without more detailed categories. It is shown that there is a lot of obviously unreasonable construction land mixed with beach and vice versa in the rough classification image. Besides, water-land alternative zone is also severely confused with construction land. So, classification only by spectral features contradicts spatial distribution of real ground cover.

3.1.2 Classification supported by spatial adjacency

The water extraction result contains both sea and pool. Only the former is retained as reference object by water pixel searching and area threshold setting for beach is adjacent to sea only. In order to avoid disturbance, pool is set as a new classification to be distinguished from sea (shown in Fig.3 (d)). To ensure the adjacent relationship of sea and beach, merge water-land alternative zone into sea to prepare for the subsequent process (shown in Fig.3 (e)). Then, starting from the merged sea, search out and mark beach pixels which adjacent to sea, and leave those not adjacent unmarked. Find out the construction land pixels inside beach area, and revise them into beach class (shown in Fig.3 (f)). lastly, search unlabeled beach pixels and revise them into construction land class. Until now, the classification revision has finished, and the final classification result is shown in Fig.3 (g).

3.1.3 Accuracy Analysis

Because the research area is small, we only select 256 sample points randomly by using ERDAS9.2 accuracy test instrument. Moreover, for all different types of ground cover in the region, selecting the same number of sample points for each type is more rational since the distribution range of each class differs greatly. Table 1 shows the error matrices of both original rough classification and classification supported by spatial adjacency.

The indicators shown in Table 1 imply that, in the original classification, the extraction accuracy of sea is good. But there are many confused construction land pixels among beach classification, and some beach pixels are misclassified into construction land. Besides, the reason why those sea pixels are misclassified into construction land are mainly due to the confusion of water-land alternative zone and construction land. All of these make the overall low accuracy of original classification, with a precision of 76.56%. After revising supported by spatial adjacency, the accuracy of beach has been significantly increased. Its pixels are classified correctly and differentiated from construction land except for some inherent misclassification. The misclassified construction land pixels inside beach are revised, water-land alternative zone are merged into sea, and the misclassified beach pixels inside construction land are also revised, making the overall accuracy up to 93.36%.

3.2 Complex experiment

To prove effectiveness and universality of the method, we also select a multi-spectral bands image of Quickbird of another coastal area, with a range of 380 m×450 m. The objects adjacent to sea contain not only beach but also vegetation. Moreover, there are shadows existing in construction land area. Both of them make this area a complex offshore area, and the diagrams of experiment on this area are shown in Fig.4.

3.2.1 Classification supported by spatial adjacency

Firstly, we still select the model of water index to extract water as the reference object. Because of the high resolution and the effects of illumination, the shadow of buildings is obvious and has the similar spectrum with the sea, so it is also extracted as the reference object together with sea (shown in Fig.4 (b)). After that, find the largest water area unit, and separate the shadow from sea by the distance to it (shown in

Table 1 Confusion matrix of simple offshore area classification results

Class	Maximum likelihood method				Total	User accuracy/%	Classification supported by spatial adjacency				Total	User accuracy/%
	Sea	Beach	Vegetation	Construction land			Sea	Beach	Vegetation	Construction land		
Sea	62	0	1	1	64	96.88	62	0	1	1	64	96.88
Beach	0	42	0	22	64	65.63	0	62	0	2	64	96.88
Vegetation	0	1	59	4	64	92.19	0	1	59	4	64	92.19
Construction land	2	24	5	33	64	51.56	2	1	5	56	64	87.5
Total	64	67	65	60	256		64	64	65	63	256	
Product accuracy/%	96.88	62.69	90.77	55			96.88	96.88	90.77	88.88		
Overall accuracy/%	76.56						93.36					

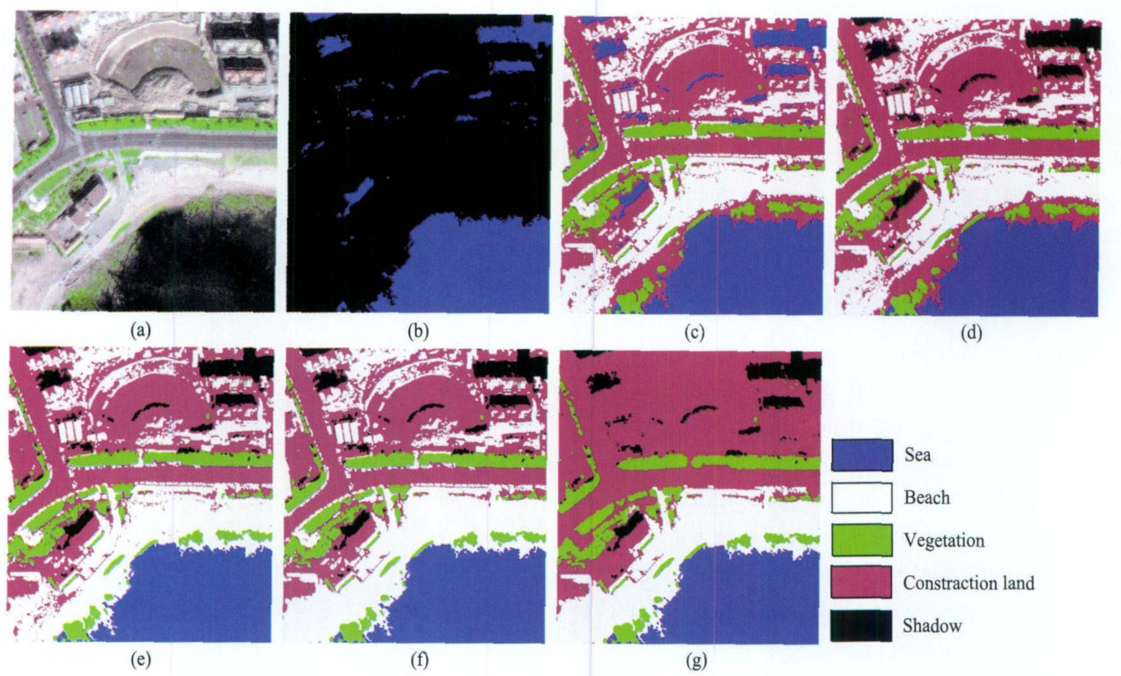

Fig. 4 Process diagram of complex offshore area classification supported by spatial adjacency

(a) Original image; (b) Water extraction; (c) Rough classification result; (d) Separation of shadow from water body; (e) Revision in intertidal zone; (f) Construction land revision inside beach; (g) Beach revision inside construction land

Fig.4 (d)). In addition, pixels are misclassified as construction land within water-land alternative zone, which should belong to beach actually. Therefore, we can use the adjacency to sea to revise them (shown in Fig.4 (e)). By now, we can also use spatial adjacency to revise construction land inside beach and beach inside construction land (shown in Fig.4 (f) (g)).

In this case, we have already identified sea water as the reference object, and searched the beach region according to it without any adjacent vegetation. Therefore, the mixed vegetation or other untargeted objects in water-land alternative zone will not interfere the revision effectiveness. However, this method is not suitable for those cases that construction land is adjacent to sea, which will lead to some wrong revisions in this way.

3.2.2 Accuracy analysis

The accuracy analysis method adopted here is the same as the one mentioned above. We select 260 random samples which distribute equally in each kind of ground. The error matrix of classification results are shown in Table 2.

The Table 2 shows that, this method could get rid of the interference of untargeted objects like vegetation, can use the distance to sea to distinguish the shadow from the sea area, which is really hard in maximum likelihood method. Thus, the overall accuracy of classification is increased greatly, from 65% to 95.38%, and the each confused classification is properly revised.

It must be pointed out that, the algorithm is to revise the target objects which have the spatial adjacent relationship on the basis of spectral rough classification, exclusive of the other objects standstill. For example, we only revise beach and construction land in this case, without sea water, vegetation and shadow. Besides, spectral confusion without spatial relationship in original classification could not be removed, which needs to develop algorithms to increase the accuracy of original classification. The revision of construction land within beach area uses the inclusion relation ship, but the misclassification due to the adjacency not the inclusion can not be eliminated, and

Table 2 Confusion Matrix of Complex Offshore Area Classification Result

Class	Maximum likelihood method					Total	User accuracy /%	Classification supported by spatial adjacency					Total	User accuracy/%
	Sea	Shadow	Beach	Vegetation	Construction land			Sea	Shadow	Beach	Vegetation	Construction land		
Sea	50	0	1	0	1	52	96.15	50	0	1	0	1	52	96.15
Shadow	51	0	0	0	1	52	0	0	51	0	0	1	52	98.08
Beach	1	0	39	0	12	52	75	1	0	50	0	1	52	96.15
Vegetation	1	0	0	48	3	52	92.31	1	0	0	48	3	52	92.31
Construction land	0	0	18	2	32	52	61.54	0	0	3	2	47	52	90.38
Total	103	0	58	50	49	260		52	51	54	50	53	260	
Product accuracy/%	48.54	0	67.24	96	65.31			96.15	100	92.59	96	88.68		
Overall accuracy/%	65							95.38						

needs some more comprehensive algorithm to revise. After the revision process of the algorithm, sea, shadow and beach could be the prior knowledge to guide the subsequent meticulous classification of vegetation and construction land. Furthermore, it is also significant in the following research of spatial relationships in small-scale accurate classification.

4 CONCLUSION AND PROSPECT

The algorithm proposed in this paper comprehensively utilizes spatial-spectral coupled information, does revision by using spatial adjacent relationship on the basis of spectral rough classification, to eliminate the inevitable confusion because of only using spectral information. This algorithm has clearly and simply represented the spatial relationships among the objects, which are more accordant with their real distributions. It operates on pixel level, which is able to search original distribution of object more comprehensively, and avoids the adverse effects due to the complex segmentation method and parameter selection in object oriented handling. This algorithm adopts index based on the multi-level model to extract reference object, whose high precision ensures the significance and accuracy of subsequent revision. Generally speaking, the algorithm is suitable for the classification of high resolution multi-spectral image, but there are still some limitations: (1) high precision of reference object is required. Otherwise, the amplifying accumulated error will occur; (2) much dependency on initial classification is demanded, otherwise, subsequent revision meaningless appears; (3) the revision to objects with inclusion relations is proceeded, otherwise, leave them standstill, which some potential error may exist. All the limitations mentioned above will be studied in the future.

Unlike traditional classification methods, the algorithm uses the prior knowledge (refer to identified reference objects in the paper) to infer the closely related objects step by step rather than directly separates all of them at one time. It provides an accurate process for classification, which is an easy-to-hard gradually controlled process and complys with the judgment habits of human vision. In the future, more diverse and accurate spatial relationship will be considered to explore its application in fine classification in small-scale for higher the accuracy. Moreover, the algorithm can also be adopted for the object oriented classification revision, and can extend to applications in agriculture land classification, building extraction in urban area.

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空间邻接支持下的遥感影像分类

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摘　要: 传统光谱分类法的局限性促使了遥感“图谱耦合”认知理论的发展, 使其更加注重了空间信息的应用。然而, 已有的分类方法虽也融入了空间形态、空间关系的应用, 在精度上有一定的提高, 但在空间规律定量描述、地物实际分布边界跟踪等方面仍存在不足。本文发展了一种空间邻接支持下的遥感影像分类方法: 通过基准地物的精确提取进而搜索与其邻接的目标地物, 对邻接范围内的地类混淆以及非邻接范围内的目标类误分一并进行修正, 并以近海地物分类为例进行试验, 获得了更为精确、合理的分类结果, 也为后续逐步精确地提取各地物提供了一种便捷有效的途径。

关键词: 遥感分类, 图谱耦合, 空间邻接, 分类修正

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1 引　言

分类一直以来都是遥感领域的一个重点和难点, 也是遥感技术到实际应用转化的一个关键步骤。然而, 以往的主流分类方法都是依据影像的光谱信息, 随着高分遥感影像技术的发展, 其造成的光谱混淆以及信息有限性的弊端表现更加明显, 遥感“图—谱”信息耦合的空间认知理论越来越受到广泛的关注和应用。

遥感数据从本质上就具有“图谱合一”的特性: 首先, “图像”是其给予人类视觉最直观的特征, 综合反映了地物空间分布的特性; 另外, “波谱”可定量反映地物形成的机理, 成为蕴含于图像之中可对地物要素进行定量表达的基本特征。因此遥感图谱耦合认知理论有机综合了遥感影像精细化辐射波谱特征和空间分布特征(骆剑承等, 2009b), 从不同角度更为全面真实地表征实际地物。

在现有许多研究中考虑到了形态、纹理等空间信息的应用, 初步实践了“图谱耦合”, 取得了一定的成效。但是, 仅这些基本空间特征对于高精度城市、海岸带等混杂型地物的分类来说, 仍难以达到实用的要求。因此, 有学者进一步采用空间关系对影像进行分类及修正, 如吴均平等依据空间距离远近关系对海岸带地类进行了划分修正; 赵红蕊等利用空间关系构造了两个波段参与分类, 实现空间约束; 蔡晓斌等利用分类影像的图斑相邻关系以及DEM信息, 对初始分类的湿地、草地和农田等地类进行修正(边馥苓和万幼, 2009; 蔡晓斌等, 2006; 陈秋晓等, 2004; 邸凯昌等 2000; Soe, 2008; 吴均平等, 2006; 赵红蕊等, 2003)。上述方法都只是部分消除了仅依赖光谱数据分类引起的同物异谱和同谱异物造成的分类错误, 但是对于空间关系的作用范围却难以较好贴合地物的实际分布。鉴于上述情况, 本文在“图谱耦合”认知理论基础上发展了一种贴合地物分布规律的空间邻接支持的分类算法, 并以近海地带为例进行试验, 获得了较好的分类结果。

2 空间邻接关系支持下的分类

2.1 空间邻接支持下的分类原理

地理学第一定律即为空间邻近, 即空间距离越近的地物具有更大的相关性(Miller, 2004; Tobler,

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第一作者简介: 乔程(1986—), 女, 博士研究生, 主要从事遥感信息提取方面的研究。

1970), 空间邻接是其中的一种具体表现方式。自然界中许多地物是关联存在的, 如沙滩与海水的关联、湿地与水体的关联等, 若其中的一种地物已确定, 则可用其作为基准地物来推断另一种地物, 即目标地物。在此, 仅探讨了对分类影像上有显著邻接关系的基准地物和目标地物两类进行搜索及标记, 并据此来确定其余地物的分布并进行相应的修正, 是一个全局性大尺度的修正。基于遥感"图谱耦合"认知理论, 本文算法在光谱粗分类基础上, 加入地物间的空间邻接关系进行修正, 其整体流程如图 1。

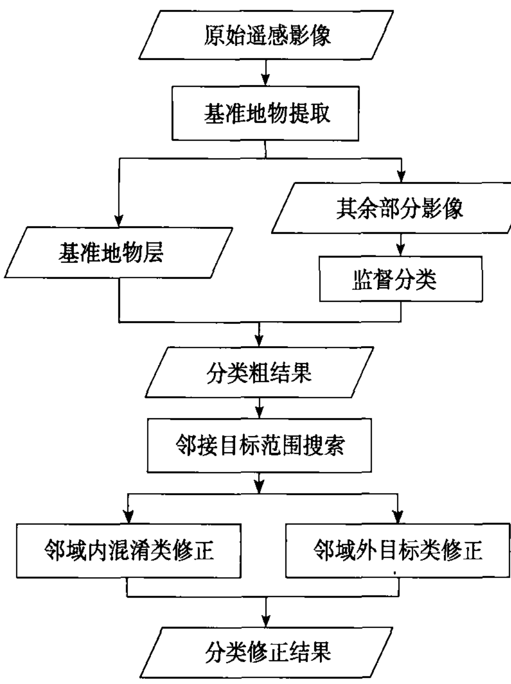

图 1 空间邻接支持的分类流程图

该算法首先从原始遥感影像上提取基准地物, 得到一景只包含基准地物的影像。用提取的基准地物对影像进行掩模操作, 得到除基准地物以外的其余部分影像, 并对该部分影像依据光谱特征, 即"谱"信息, 进行监督分类。然后, 将部分影像的监督分类结果与基准地物层合并, 得到整景影像的一个粗分类结果。进而, 在粗分类影像基础上再利用地物的空间邻接关系, 即"图"信息, 搜索与基准地物邻接的目标地物并确定其分布范围, 并依据目标地物的搜索范围来确定各地类的实际分布并作相应的修正, 从而得到一个更贴合实际、精度更高的分类结果。

2.2 基准地物高精度提取方法

基准地物一般选取影像上具有独特的光谱特性, 集中分布并且易于提取的地物, 比如水体。它在整个算法中作为先验知识存在, 其精度也决定了后续分类修正的改进程度, 因此, 对基准地物的提取精度要求较高。

基准地物因其特性一般采用单波段阈值法、波段间的差/比值法等进行提取, 而近来发展并被广泛采用的指数法不失为一种便捷高效的方法。然而, 仅采用指数还不足以精确提取边界, 本文便采用了基于指数的多层次专题信息提取模型(图 2)来提取基准地物, 在指数表征的地物波谱特性基础上, 又融入了分层分类法, 进一步通过空间上的逐步分级逼近基准地物的空间分布。

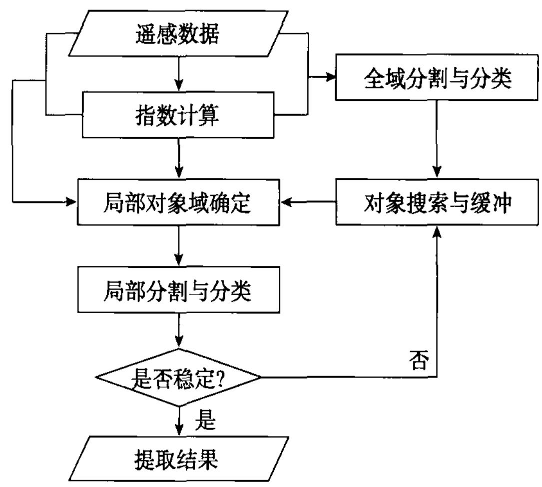

图 2 基准地物高精度提取模型

该模型首先在原始遥感数据上, 进行基准地物的指数计算, 获得全域范围内基准地物信息的定量化增强; 第 2 步, 对指数计算后的波段进行分割, 初步获得基准地物与背景的分离, 然后在分割图像上进行基准地物与背景样本信息的自动选择, 加入更多图像波段, 采用分类器进行图像分类, 获得全域范围基准地物的提取; 第3 步, 在全域基准地物提取的基础上, 搜索各基准地物单元的局部空间位置, 并通过对各单元进行缓冲区分析, 选择确定局部信息提取的各个基准地物区域; 最后, 在各个局部区域内, 不断迭代重复图像分割和分类的过程, 逐步实现对基准地物精细提取结果的逼近(骆剑承等, 2009a)。

2.3 空间邻接支持下的分类修正算法

粗分类影像上, 每种地类具有不同属性值, 空间邻接分类修正算法正是依据该值来搜索和判别地类, 进而通过改变该值达到修正目的。该算法仍是在像元级层次上操作, 主要过程描述如下:

(1) 基准地物搜索: 首先遍历粗分类影像, 依据基准地物的属性值 O 搜索基准地物像元, 同时, 可

根据需要利用面积大小或距离远近的阈值进行一定的排除，以避免噪音带来的干扰，从源头确保精度；

(2) 基准地物纯化：若有需要，可先对搜索到的基准地物进行邻接修正，将其与目标类间的混淆类像元赋予属性值 O，归并到基准地物，以做纯化，确保基准地物与目标地物的邻接关系；

(3) 目标地物搜索与标记：从修正后的基准地物出发，依据目标类属性值 T，以八邻域方式搜索与基准地物邻接的目标地物像元，并将其标记为 TRUE，不相邻的目标类像元则不予标记；

(4) 混淆类修正：在标记为 TRUE 的目标类区域中，搜索其中包含的其他混淆地类，将混淆类像元赋予目标类属性值 T 以作修正；

(5) 目标类误分修正：依据属性值 T 搜索未被标记为 TRUE 的目标类像元，即为非基准地物邻接区域内的目标类误分，将其属性值赋予相应实际地类的属性值即可完成分类修正。

3 近海地带分类试验

3.1 简单型近海地带试验

该试验区为国内某近海地带范围为海域和陆地距离各 1.5 km 左右，面积约 10 km^2 的区域。试验所用的遥感信息源为夏季的一景福卫二号影像(图 3 (a))，采用多光谱波段，分辨率为 8 m。该区域为海水向陆地的典型简单过渡带，存在着一些交互、易混淆的地物，如水陆交互带、沙滩与城市用地中的道路、建筑物等，使传统的光谱分类法在该区域应用中存在诸多混淆；然而，遥感影像中所蕴含的“图”信息在此表现显著：地物间存在着紧密的邻接与层次关系，混淆地物虽光谱相似但分布位置不同，如海水、水陆交互带与沙滩相邻接，沙滩不存在于非邻海市区等。因此，空间邻接关系辅助光谱分类，也即“图谱耦合”的分类方法的应用在此是十分必要且有效的。

3.1.1 基准地物提取与初分类

据前所述基准地物的特性，本例中选取海水作为基准地物，因此首先要对其进行精确的提取。利用前述基准地物高精度提取方法，在此针对水体的指数计算采用归一化水体指数法(NDWI)(徐涵秋，2005)，其公式如下：

$$\mathrm{NDWI}=\frac{\mathrm{GREEN}-NIR}{\mathrm{GREEN}+NIR}$$

式中，GREEN 代表绿波段，NIR 代表近红外波段。将水体精确地提取出后(图 3(b))，再将水体层作为掩模

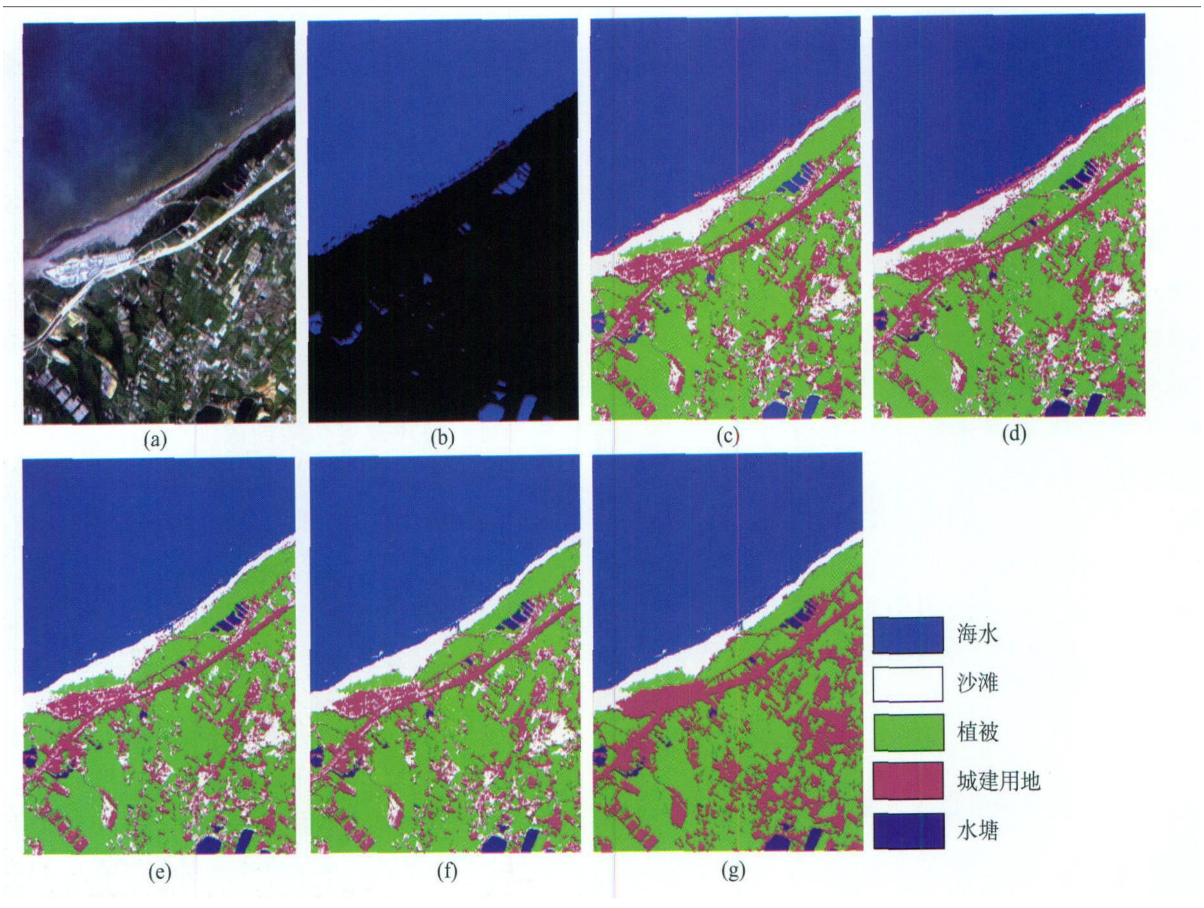

图 3　空间邻接支持下的简单近海地带分类修正过程图
(a) 原始影像；(b) 水体提取；(c) 分类粗结果；(d) 海与水塘分离；(e)水陆交互带修正；(f) 沙滩区建筑物修正；(g) 建筑物区沙滩修正

对剩余部分影像采用最大似然法进行监督分类, 得到整景影像的一幅初始粗分类图(图 3(c))。该算法为全局性大尺度修正, 因此采用的分类体系仅包含了水体、沙滩、植被与城建用地(主要为道路和建筑物)4 个大类, 而未作细分。可以看出, 沙滩中混杂有城建用地类别, 而城建用地中也混杂了大量的沙滩类别, 这是明显不合理的; 此外, 水陆交互地带与城建用地也存在严重的混淆, 因此, 仅依靠光谱特性的分类与实际地物的空间分布存在较大出入。

3.1.2 空间邻接支持下的分类

水体提取中将海水与水塘等都提取出来, 而沙滩仅与海水相邻, 因此, 通过水体像元搜索及面积阈值设定, 仅保留海水作为沙滩搜索的基准地物, 而将水塘作为新的一类地物区别开来(图 3(d))。为确保海水与沙滩的邻接关系, 将水陆交互带归并到海水中以便于后续处理(图 3(e))。然后, 由修整后的海水出发, 将与海水邻接的沙滩类像元搜索出来并做标记, 不邻接的沙滩类像元则不予标记。搜索标记的沙滩区域中包含的城建用地像元, 将其修正为沙滩类(图 3(f))。最后, 搜索未做标记的沙滩类像元, 并将其修正为城建用地类, 即完成本次分类修正过程, 得到最终的分类结果(图 3(g))。

3.1.3 精度分析与讨论

因研究区范围较小, 利用 ERDAS9.2 的精度检验工具随机选取 256 个检验点; 又因该区各地类覆盖范围差异较大, 对各类选取相同数目的检验点以保证检验的合理性, 对初始粗分类和空间邻接支持下的分类结果进行精度评价, 得到的分类误差矩阵结果如表 1。

由分类评估结果的各项指标可以看出, 初始粗分类中, 海水的提取精度较好, 但沙滩中含有许多误分的城建用地类, 有些沙滩也被分到城建用地中去; 海水中误分为城建用地的像元, 主要是因水陆交互带与城建用地的混淆造成的, 从而导致初始分类的整体分类精度也较低, 为 76.56%。经空间邻接关系修正后, 沙滩的分类精度得到显著提高, 除少许固有误分外, 该类样本点都已被正确归类, 与非邻海区的城建用地区分开来, 其中混淆的城建用地类也被修正; 水陆交互带被归并到海水中, 消除了城建用地中的沙滩误分, 从而整体分类精度也得到显著提高, 达到 93.36%。

3.2 混杂型近海地带试验

为了验证本文方法的有效性和普适性, 又选取了另一沿海区域的 Quickbird 多光谱影像进行试验, 试验区范围约为 380m× 450m。该研究区与海相邻的区域不仅有沙滩, 也有较多植被, 此外建筑物区还存在着阴影, 视为混杂型的近海地带。利用本文方法对该地区的试验过程如图 4。

3.2.1 空间邻接支持下的分类

首先, 仍采用基于水体指数的模型提取海水作为基准地物。因高分辨率影像以及光照的因素, 建筑物形成的阴影较为明显, 且阴影与建筑物光谱相近, 因此将其与海水一同作为基准地物提取出来(图 4(b))。对此, 选取面积最大的水域确认为海水, 通过与其距离的远近即可将阴影分离(图 4(d))。此外, 海陆交互带处误分为城建用地的部分, 实际地物主要是沙滩, 因此利用与海的邻接关系将其修正(图 4(e))。至此, 便可利用与海的邻接关系对沙滩区的建筑物以及建筑物区的沙滩误分进行修正(图 4(f)和图 4(g))。

本例中, 在确定了海水这一基准地物后, 便据其搜索沙滩类, 对与之邻接的植被类则不予搜索与处理, 从而, 水陆交互带处混杂的植被(或其他非目标地类)对本方法的修正效果不会产生干扰。然而, 本方法不适用于建筑物区与海邻接的情况, 会造成一定误修正。

3.2.2 精度分析与讨论

本研究区试验精度评价同前例, 选取 260 个随机点, 均衡分布到各地类, 得到的分类误差矩阵结果如表 2。

表 1 简单型近海地带分类结果误差矩阵

类别	最大似然分类				总计	用户精度/%	空间邻接支持下的分类				总计	用户精度/%
	海水	沙滩	植被	城建用地			海水	沙滩	植被	城建用地		
海水	62	0	1	1	64	96.88	62	0	1	1	64	96.88
沙滩	0	42	0	22	64	65.63	0	62	0	2	64	96.88
植被	0	1	59	4	64	92.19	0	1	59	4	64	92.19
城建用地	2	24	5	33	64	51.56	2	1	5	56	64	87.5
总计	64	67	65	60	256		64	64	65	63	256	
生产精度/%	96.88	62.69	90.77	55			96.88	96.88	90.77	88.88		
总精度/%				76.56						93.36		

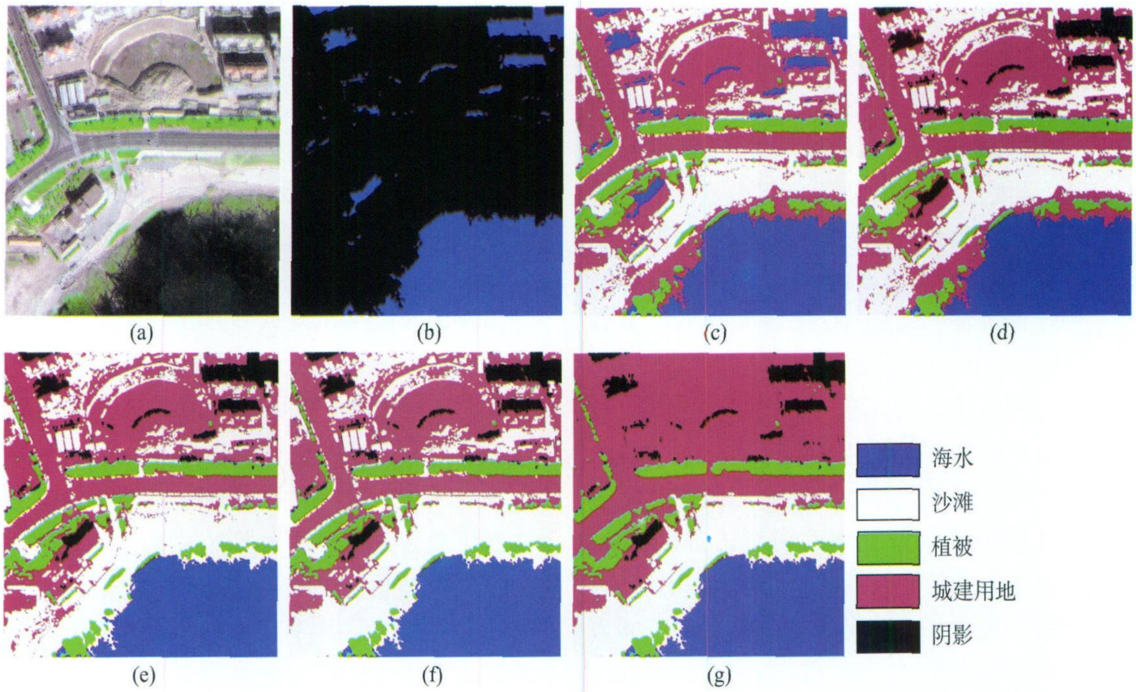

图 4 空间邻接支持下的混杂近海地带分类修正过程图

(a) 原始影像; (b) 水体提取; (c) 分类粗结果; (d) 水与阴影分离; (e) 水陆交互带修正; (f) 沙滩区建筑物修正; (g) 建筑物区沙滩修正

表 2 混杂型近海地带分类结果误差矩阵

类别	最大似然分类					总计	用户精度/%	空间邻接支持下的分类					总计	用户精度/%
	海水	阴影	沙滩	植被	城建用地			海水	阴影	沙滩	植被	城建用地		
海水	50	0	1	0	1	52	96.15	50	0	1	0	1	52	96.15
阴影	51	0	0	0	1	52	0	0	51	0	0	1	52	98.08
沙滩	1	0	39	0	12	52	75	1	0	50	0	1	52	96.15
植被	1	0	0	48	3	52	92.31	1	0	0	48	3	52	92.31
城建用地	0	0	18	2	32	52	61.54	0	0	3	2	47	52	90.38
总计	103	0	58	50	49	260		52	51	54	50	53	260	
生产精度/%	48.54	0	67.24	96	65.31			96.15	100	92.59	96	88.68		
总精度/%					65							95.38		

从上表中可以看出，除展示本算法不受植被等非目标类的干扰外，本例采用距海水的远近将最大似然法无法区分的海水与阴影区分开来，从而综合地使整体的分类精度得到了很大提升，从 65%提高到 95.38%，各混淆地类也得到了较好的修正。

需要说明的是，本文算法仅是在光谱粗分类基础上，对存在空间邻接关系的目标地物进行修正，而对其余地物则维持原状，未做修正。如仅对沙滩和城建用地进行了修正，而对海水、植被及阴影则未做处理。此外，对初始分类中不具有空间关系的光谱混淆也无法消除，需要深入发展提高初始分类精度的算法；对沙滩区城建用地的误分修正利用的是前者对后者的包含关系，对于相邻但未包含的潜在误分还未能消除，需进一步发展更为全面的算法。而该算法完成修正过程后，即可将海水、阴影及沙滩作为先验知识，指导后续对植被、城建用地的精细分类，并可进一步挖掘小尺度精细分类中的空间关系，发展具有针对性的高精度精细分类。

4 结论与展望

本文算法综合运用了遥感“图谱耦合”信息，在光谱特征粗分类的基础上，利用空间邻接关系进一步修正，消除了仅由光谱造成的不可避免的混淆。该算法清晰、简练地表征出了地物间的空间关系，更符合地物的实际分布。其中，在像元级上进行处理，能更全面地搜寻地物的原始分布范围；避免了对象级处理中的分割方法和参数选择复杂等因素所造成的影响；此外，采用基于指数的多层次提取模型提取基准地物，令其精度更高，进而有效保障了

后续修正的意义和精度。该算法适用于分辨率较高的多光谱影像，其中也存在以下几方面的缺陷有待进一步解决和研究：(1)对基准地物的精度要求高，否则，累积误差将更大；(2)对初始分类效果的依赖性较大，初始分类结果决定着修正结果的改进意义；(3)在目标地物范围内包含的地类进行修正，对相邻但不包含的混淆地物则未予修正，存在一定的潜在误差。

有别于传统的遥感分类，该算法不是一次性地将所有地物分出来，而是根据已确定的基准地物来推断与其有紧密邻接关系的地物，即利用先验知识来支持后续地物的判别分类，可避免干扰，并将各地物高效地提取出来。该过程是一个由易到难、逐步可控的、精确的提取过程，也更符合人眼视觉的判断推理过程。后续将进一步挖掘更全面、准确的空间关系的应用，并探索其在小尺度精细分类中的应用，以辅助进行全域精细尺度的高精度分类。该算法在处理层次上，适用于象级分类修正；在应用领域中，可推广应用到诸如农业用地分类、城市建筑物提取等方面。

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