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Landuse Information Quick Mapping Based on Low Altitude Remote Sensing Technology and Transfer Learning

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Abstract: Obtaining surface spatio-temporal data rapidly, automatically and accurately is an important issue in agriculture informationization and intellectualization. Samples obtained by manual and conventional manual visual interpretation are difficult to adapt the demands of current agricultural land resources information automatic extraction. At the same time, low altitude remote sensing technology as a kind of emerging technology for earth observation in recent years, with its flexibility, high efficiency, low cost, was widely used in the investigation of all kinds of resources. If only extraction information from single phase image, regardless of the historical image data set information extraction has been completed, it will cause information waste and repeated work. Based on this, spatio-temporal data mining technology was introduced, and related knowledge transfer learning mechanism was used, a novel landuse information classification method based on knowledge transfer learning (KTLC) was proposed. Firstly, new image was segmented by improved mean shift algorithm to obtain image objects. Secondly, the vector boundary of the objects and former historical landuse thematic map were matched and nested, invariant objects were obtained through overlay analysis, and purification of invariant object was finished by spectral and spatial information threshold filtering. The historical features category knowledge of thematic map was transferred to the new image objects. Finally, current images classification mapping was completed based on decision tree, and landuse classification mapping results were completed by the KTLC and eCognition for landuse information mapping classification (EC). The experimental results showed that KTLC could obtain accuracies equivalent to EC, and also outperforms EC in terms of efficiency.

Key words: low altitude remote sensing technology; landuse information; classification mapping; invariant objects acquisition; knowledge transfer learning; prior knowledge

0 Introduction

It is an issue in agricultural informatization and intellectualization to collect surface spatio-temporal data rapidly and accurately. In general, the data sources selected during agricultural information background investigations (such as basic farmland area monitoring and crop planting structure investigation) are satellite images[1-5]. However, it is hard to collect the required image data continuously in cloudy and foggy regions (such as Sichuan Basin) as satellite sensors are affected by weather conditions. Satellite images generally have low spatial resolution, so it is hard to identify the scattered and discontinuous small pieces of cultivated land for precise agricultural land monitoring[6-7]. Meanwhile, land use information is still obtained and updated by means of manual interpretation currently, resulting in large workload and low efficiency. Although some scholars have proposed the automatic interpretation method, large workload is also required for manual sampling. Therefore, it is far behind real automation. In consequence, higher requirements are placed on data source resolution and information extraction technologies. Under such

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circumstance, low-altitude remote sensing technology represented by UAVs emerges. Compared with the conventional aerial photography crafts, UAVs have the following advantages: rapid take-off and landing, repetitive operations; low cost for image collection; high spatial resolution of collected images[8-10]. As the UAV equipped with the low-altitude remote sensing technology can provide images with centimeter-level resolution at low cost, it has great application potential for basic farmland protection areas with high requirements on accuracy of land use information.

With rapid development of remote sensing technologies, the spatial resolution of collected remote sensing images is increasingly high. On the high-resolution images collected by applying low-altitude remote sensing technology, more spectral information of surface features can be obtained, spectra difference of similar surface features become large while that of different land types is reduced. Besides, the phenomenon of same feature with different spectrums and different features with same spectrum become more common. Due to a number of details identified on images and the complication of spectral characteristics of surface features, the accuracy of classification methods (such as maximum likelihood method, minimum distance method and k-means clustering algorithm) based on conventional spectrum statistics characteristics is lowered[11]. BAATZ et al.[12] put forward the object-oriented remote sensing image classification method based on the characteristics of high-resolution images. With the growing popularity of images with high spatial resolution, the object-oriented analysis method is gradually replacing the conventional pixel-based analysis method[13]. With the objectification technology, spectra, shape and texture information can be collected effectively and further integration of hierarchical relationships or semantic information can be realized. Therefore, it is more aligned with the visual image interpretation principles and process[14-15]. A number of studies[16-18] prove that the object-oriented classification method has great potential in improvement of automatic extraction of high-resolution remote sensing images and that it is an ideal choice for automatic classification of high-resolution images.

Current knowledge transfer methods can be classified into 4 categories, i. e., instance transfer, characteristics transfer, parameter transfer and associated-knowledge transfer[19-20]. By combining associated-knowledge transfer, a transfer method for surface feature category labels (associated knowledge) based on detection of invariant objects is designed for classified mapping of high-resolution images collected by applying the low-altitude remote sensing technology. The "category interpretation knowledge of invariant surface features" is migrated from the source domain to the target domain by obtaining invariant surface features on new images through matching and nesting of the new land use images and the previous time-phase thematic vector maps and by transferring the surface feature category label knowledge integrated in the previous time phase to the new images. It is used to set up a new characteristic-surface feature mapping relationship. In this way, this paper proposes a method for classified mapping of land use information on high-resolution remote sensing images.

1 General information on study area and data

The study area is located in the basic farmland protection area in Lianshan town, Guanghan city, Deyang city. The parent materials of soils in Guanghan city are either weathered bedrock matters or loose deposits. The area with soil thickness greater than 100 cm and less than 30 cm respectively takes up 7.43% and 1.5% of the total cultivated area. Most soils feature good arability, long arable period and good fertilizer preservation & supply performance, providing a large arable area. However, Guanghan city has a large population with relatively less land. It covers 548 km^2 in total with a total population of 600 000. Its agricultural area is only 34 000 hm^2, with cultivated land area of 3.1 hm^2 and basic farmland protection area of 28 000 hm^2. Based on the state standards for land use classification and in combination with local conditions, the study area mainly includes 6 categories of land, i. e., cultivated land, forest land, residential land, road, water and other land. Seen Fig. 1 for location of the study area.

Considering that the study area is gentle in terrain and therefore convenient for takeoff and landing, the ejection-type fixed-wing UAV is selected for the experimental purpose. Canon EOS 5D Mark Ⅱ is carried on the flying platform and the preset forward overlap and side overlap are 75% and 45% respectively. The flight altitude is 600 m and the camera focal length is 24.49 mm. The collected UAV images have a spatial resolution up to 0.2 m. The thematic land use maps in previous time phase were drawn in June 2014, as shown in Fig. 2a and 2b. They were taken by UAV in July 2015. To better verify efficiency and applicability of the method, two typical hybrid UAV images of different land types (i. e., "complex building - cultivated land" hybrid image as shown in Fig. 2c and "forest land - cultivated land" hybrid image as shown in Fig. 2d) are selected.

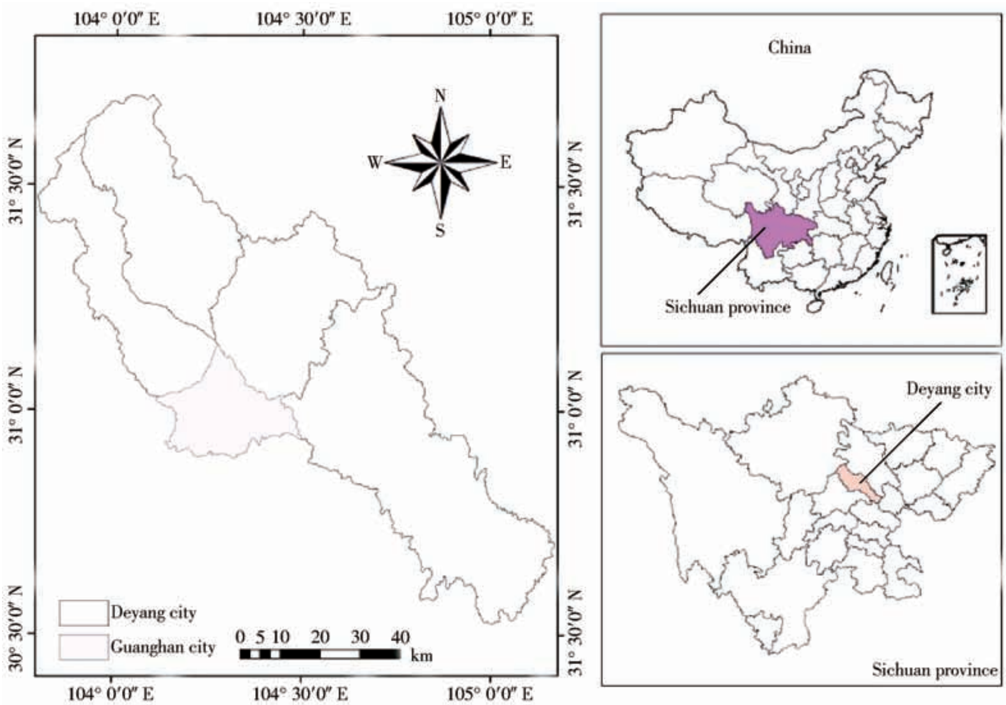


Fig. 1 Location of Guanghan city selected for experimental purpose

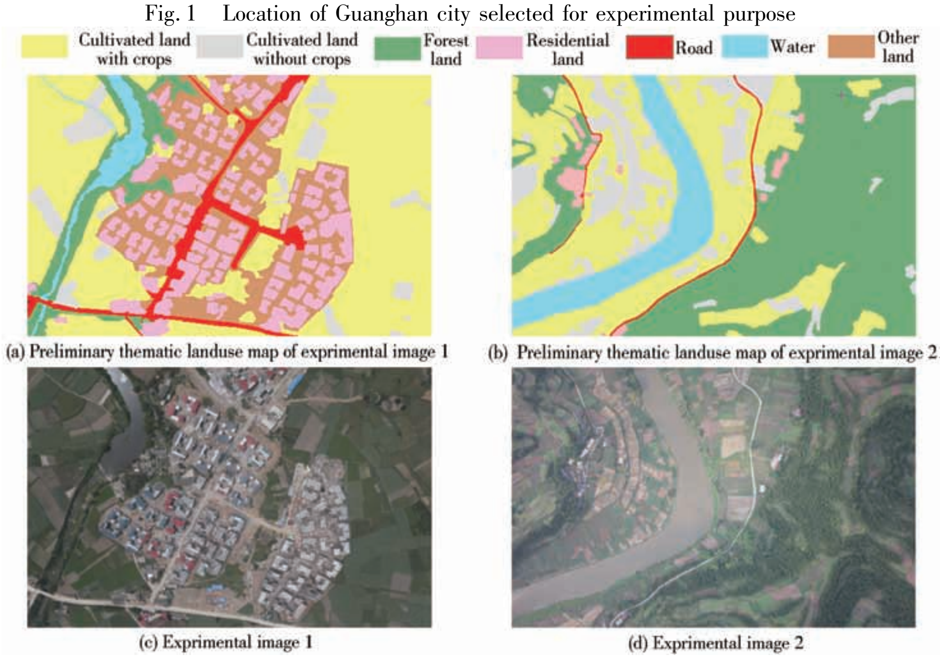


Fig. 2 Preliminary thematic landuse maps and experimental UAV images

2 Working process and study method

2.1 Working process

The collected original UAV images are preprocessed, including color uniformizing, light uniformizing and generation of orthoimages. After preprocessing, image objects are identified after multi-resolution segmentation of the to-be-classified images by applying the improved mean shift algorithm. Next, the vector boundaries of segmented objects are matched and nested with the thematic land use maps in previous time phase. Invariant objects on current images are identified through overlay analysis so as to weed out wrong invariant objects based on spectral and spatial information thresholds. At last, the categories of invariant surface features are transferred to the current target images through transfer learning. Classification rules are established with the decision tree so as to carry out classified mapping with current images rapidly. In addition, a comparison is made with the classified mapping directly using object-oriented classification software (eCognition).

2.2 Preprocessing of image data

The digital camera on UAV is of non-metric type, so the images are subject to serious lens distortion. Therefore, distortion correction shall be carried out based on distortion parameters of the camera[21-22]. Meanwhile, exposure time intervals and different weather conditions in the flight course will result in chromatic aberration, so color and light uniformizing shall be carried out with the mask method. Based on the aircraft attitude parameters recorded by the flight control system, preliminary image sorting and positioning can be carried out for matching homologous points of adjacent image pairs. After matching of homologous points, block adjustment can be made based on the conditions of collinearity equation. After that, the coordinates of ground control points may be incorporated to realize absolute orientation so as to obtain the corrected orthoimages. It provides high-accuracy orthoimage data for subsequent rapid updating and mapping of land use information.

2.3 Mapping method (KTLC) of land use information based on transfer learning

2.3.1 Calculation of improved mean shift segmentation and image/spectral features of objects

First of all, the preprocessed UAV images are divided into texture domain and homochromatic domain. The latter is obtained by applying the mean shift algorithm directly while the former is segmented by applying the mean shift algorithm after appropriate bandwidth is obtained based on normalized distribution density. Next, based on the established cost function, a decision on merging of adjacent domains is made to eliminate over-segmentation domain. Refering to reference [23] for the improved mean shift segmentation algorithm selected in this paper. Afterwards, the vector boundaries of segmented objects are matched and nested with the thematic land use maps in previous time phase, allowing them to be under the consistent spatial reference conditions. Invariant objects are further identified on the current images through overlay analysis. After image segmentation, object features have to be calculated so as to ensure smooth progress of the subsequent classification work. In this paper, totaly 18 features listed in Tab. 1 are calculated based on spectral, shape and textural features.

Tab. 1 Spatial and spectral features of objects

Spectral features			Shape features			Textural features		
Description	Spectrumor space	Interpretation	Description	Spectrumor space	Interpretation	Description	Spectrumor space	Interpretation
R_Mean	Spectrum	Mean value of red spectral band	L/W	Space	Length - width ratio	GLCM_H	Space	Homogeneity
G_ Mean	Spectrum	Mean value of green spectral band	Geo_L	Space	Object length	GLCM_E	Space	Entropy
B_ Mean	Spectrum	Mean value of blue spectral band	Geo_W	Space	Object width	GLCM_C	Space	Contrast ratio
R_Dev	Spectrum	Standard deviation of red spectral band	Border_L	Space	Side length of object	GLCM_V	Space	Variance
G_ Dev	Spectrum	Standard deviation of green spectral band	Compact	Space	Compactness	GLCM_D	Space	Heterogeneity
B_ Dev	Spectrum	Standard deviation of blue spectral band	Num_P	Space	Number of pixels	GLCM_A	Space	Angularsecond moment (ASM)

2.3.2 Purification of invariant object samples

It shall be noted that a mistake may be made when invariant objects on the current images are identified through overlay analysis. To this point, relevant rules shall be designed to weed out wrong invariant objects. In this paper, invariant objects are purified based on spectral and spatial information. Specifically, object purification is judged by calculating the distance (difference value) between the mean brightness of image elements and the center of object brightness value (mean value), as

$$\begin{cases} \| R_{x_i} - M_{\mu_i} \| \leqslant 4\delta_i \\ \| G_{x_i} - M_{\mu_i} \| \leqslant 4\delta_i \\ \| B_{x_i} - M_{\mu_i} \| \leqslant 4\delta_i \end{cases} \tag{1}$$

where, R_{x_i}, G_{x_i}, B_{x_i} is object brightness in red, green and blue spectral bands, respectively; M_{μ_i} is mean value of object sample brightness; δ_i is spectral standard deviation of image elements in each object.

Considering the spatial information, a wrong object can be judged by checking whether the spectral standard deviation of image elements in each object exceeds the limits, as

$$\begin{cases} \delta_i \leqslant 0.2 R_{b_{\max}} \\ \delta_i \leqslant 0.2 G_{b_{\max}} \\ \delta_i \leqslant 0.2 B_{b_{\max}} \end{cases} \tag{2}$$

where $R_{b_{\max}}$, $G_{b_{\max}}$, $B_{b_{\max}}$ is the maximum image brightness in red, green and blue spectral bands respectively.

If the selected invariant object meets both Eq. (1) and Eq. (2), it is a reliable invariant object; otherwise, it is an unreliable invariant object and shall be weeded out.

2.3.3 Associated-knowledge transfer learning and rapid classified mapping

After collection and purification of object samples regarding current target images, the best feature combination and classification model are selected for supervised classification based on the calculated image and spectral features. There are many methods regarding feature optimization selection and classification models. To ensure simplification while considering efficiency, the practice regarding feature optimization selection and classification model is conducted by adopting the decision tree algorithm. Then, judgment rules are established for classification purpose so as to complete classified mapping of current images.

2.4 EC method

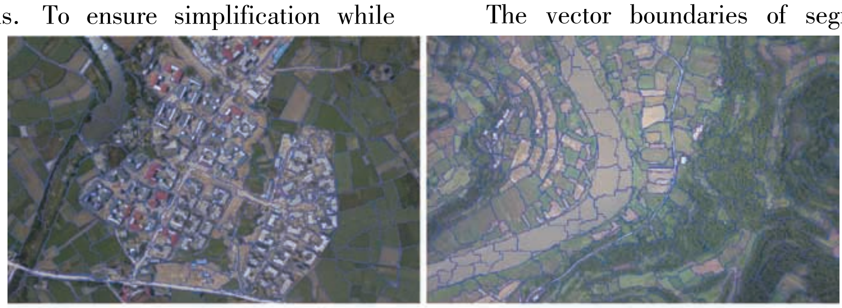
To verify reliability of the proposed method, classified mapping of land use information is carried out with the widely applied eCognition 8 and a comparison is made with the results obtained from the KTLC method. Image segmentation shall be conducted, and then classified mapping of the segmented image objects may be carried out. Given that the standard nearest neighbors classification method is simple, efficient and extensively applied, it is adopted for classified mapping with the EC method in this paper. Specific mapping method is as follows: first, select a sample object and carry out statistic analysis to obtain textural/spectral/shape features, information on adjacent domains, etc. for establishment of multi-dimensional feature space. Second, calculate the distance between the to-be-classified object and the sample. Finally, judge which one of the to-be-classified objects is closest to a sample based on feature distance relationship and membership function, and then incorporate such object into the corresponding category.

3 Results and analysis

3.1 Rapid classified mapping

Based on the principles in Section 2.1, spectral and spatial scale parameters are taken as 7 and 10 respectively for the improved mean shift segmentation. The segmentation results obtained by applying the improved mean shift algorithm are shown in Fig. 3.

The vector boundaries of segmented objects are



(a) Segmentation result of exprimental image 1 (b) Segmentation result of exprimental image 2

Fig. 3 Segmentation results based on improved mean shift method matched and nested with the thematic land use maps obtained in June 2014. Invariant objects are identified through overlay analysis and purified based on spectral and spatial information to weed out the wrong ones. In addition, the categories of invariant surface feature objects are transferred to the current target images through knowledge transfer learning. Finally, the image/spectral features of invariant objects are subject to optimization selection by using a decision tree. Classification rules are established for classified mapping of land use information. Seen Fig. 4a and Fig. 4b for the results of classified mapping with the KTLC method.

In the experimental process, segmentation parameters settings are as follows based on the principles in Section 2.3: segmentation scale parameter: 90; color/shape parameter: 0.5/0.5; smoothness/compactness parameter: 0.5/0.5. Seen Fig. 4c and Fig. 4d for the results of classified mapping of land use information with the EC method.

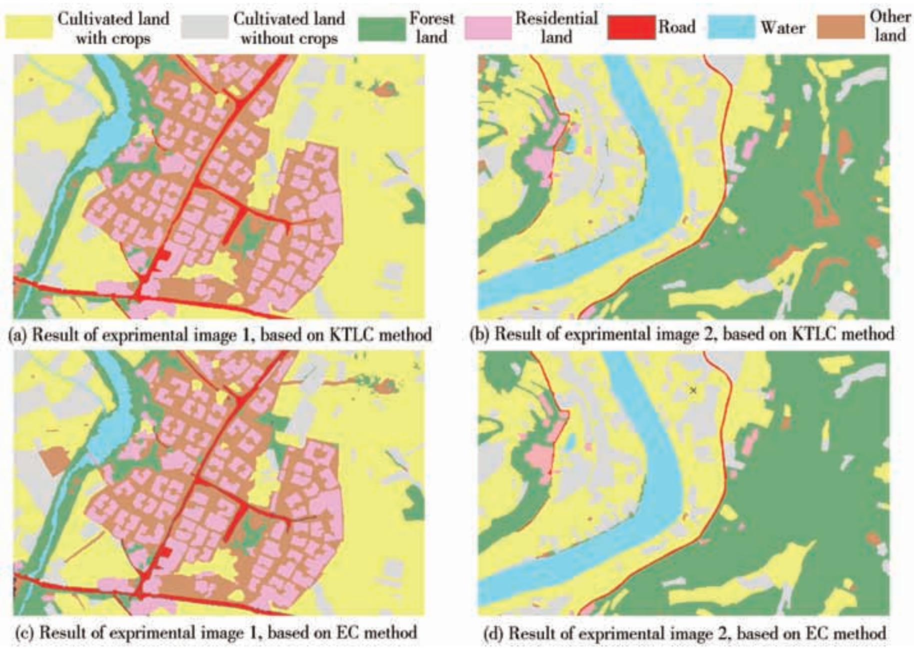


Fig. 4 Results of classification mapping based on two methods

3.2 Evaluation on precision and efficiency

In general, the precision evaluation of classification results is classified into qualitative evaluation and quantitative evaluation. For qualitative evaluation, a consistence comparison between the pattern spots after classification and the actual surface feature is mainly carried out. It is strongly subjective. For quantitative evaluation, overall precision, Kappa coefficient and the like are mainly calculated[24-25]. Due to high spatial resolution of UAV images, verification data can be directly obtained through visual interpretation. To get more objective evaluation results, verification points are obtained with the following method in this paper: first, draw a 20×20 regular grid with an area equal to the image area in the experiment; then, generate 10 random points in each grid; finally, determine the land use type at each random verification point through visual interpretation. For experimental image 1, totally 395 valid verification points are obtained; for experimental image 2, totally 382 valid verification points are obtained. These verification points are overlapped with the classification results to judge whether the results of classified mapping are correct. Upon calculation, for experimental image 1, the overall classification precision of the KTLC method is 88.61% and the Kappa coefficient is 0.86; the overall classification precision of the EC method is 89.87% and the Kappa coefficient is 0.87. Seen Tab. 2 and Tab. 3 for detailed results. For experimental image 2, the overall classification precision of the KTLC method is 88.30% and the Kappa coefficient is 0.82; the overall classification precision of the EC method is 84.84% and the Kappa coefficient is 0.79. Seen Tab. 4 and Tab. 5 for detailed results.

Experimental image 1 is a "complex building-cultivated land" hybrid image. It can be learned from Tab. 2 and Tab. 3 that the KTLC method and the EC method have high separation precision in terms of

Tab. 2 Confusion matrix of accuracy for experimental image 1 (KTLC method)

	Forest land	Cultivated land with crops	Cultivated land without crops	Road	Residential land	Other land	Water
Forest land	43	12	1	0	2	0	0
Cultivated land with crops	2	106	0	0	0	0	0
Cultivated land without crop	0	4	36	0	1	2	0
Road	0	0	0	18	5	3	0
Residential land	0	0	0	2	82	3	0
Other land	2	0	5	1	0	53	0
Water	0	0	0	0	0	0	12
Producer's precision/%	91.49	86.89	85.71	85.71	91.11	86.89	100
User's precision/%	74.14	98.15	83.72	69.23	94.25	86.89	100
Overallprecision is 88.61% Kappa coefficient is 0.86							

Tab. 3 Confusion matrix of accuracy for experimental image 1 (EC method)

	Forest land	Cultivated land with crops	Cultivated land without crops	Road	Residential land	Other land	Water
Forest land	46	6	0	0	0	0	0
Cultivated land with crops	3	101	0	0	0	0	0
Cultivated land without crop	0	4	30	0	0	4	0
Road	0	0	0	14	4	2	0
Residential land	1	0	1	3	90	4	0
Other land	1	0	6	0	0	63	1
Water	0	0	0	0	0	0	11
Producer's precision/%	90.20	90.99	81.08	82.35	95.74	86.30	91.67
User's precision/%	88.46	97.12	78.95	70.00	90.91	88.73	100
Overallprecision is 89.87% Kappa coefficient is 0.87							

Tab. 4 Confusion matrix of accuracy for experimental image 2 (KTLC method)

	Forest land	Cultivated land with crops	Cultivated land without crops	Road	Residential land	Other land	Water
Forest land	137	11	0	0	1	0	0
Cultivated land with crops	15	82	2	0	0	0	0
Cultivated land without crop	0	4	59	0	0	2	0
Road	0	0	0	11	2	0	0
Residential land	2	0	0	2	15	1	0
Other land	1	0	6	0	1	12	0
Water	0	0	0	0	0	0	16
Producer's precision/%	88.39	84.54	88.06	84.62	78.95	80.00	100
User's precision/%	91.95	82.83	90.77	84.62	75.00	60.00	100
Overallprecision is 88.30% Kappa coefficient is 0.82							

Tab. 5 Confusion matrix of accuracy for experimental image 2 (EC method)

	Forest land	Cultivated land with crops	Cultivated land without crops	Road	Residential land	Other land	Water
Forest land	141	10	2	0	0	1	0
Cultivated land with crops	20	74	0	0	0	0	0
Cultivated land without crop	0	1	51	0	1	2	0
Road	0	0	0	8	4	1	0
Residential land	1	0	0	1	16	2	0
Other land	4	0	7	1	0	14	0
Water	0	0	0	0	0	0	15
Producer's precision/%	84.94	87.06	85.00	80.00	80.00	70.00	100
User's precision/%	91.56	78.72	92.73	61.54	80.00	53.85	100
Overallprecision is 84.8% Kappa coefficient is 0.79							

building land, cultivated land with crops and without crops. It indicates that these three types of land are highly separable on such images with high spatial resolution. In the KTLC method, the classification precision of forest land and road is 74.14% and 69.23% respectively, which is lower than that of the EC method. However, its classification precision of any land types is not extremely low and it has high classification precision in terms of cultivated land with crops, building land and waters (98.15%, 94.25% and 100% respectively). As a result, the overall precision of the KTLC method is up to 88.61%, which is comparable with that (89.87%) of the EC method. Experimental image 2 is a "forest land – cultivated land" hybrid image. It can be learned from Tab. 4 and Tab. 5 that both the KTLC method and the EC method result in many errors in separation of forest land and cultivated land with crops due to high spectrum and texture similarity of these two types of land. The classification precision can be improved if more reliable samples are used during transfer learning. The overall precision of the KTLC method is 88.30%, which is slightly higher than that (84.84%) of the EC method, especially for forest land, cultivated land without crop and water (91.95%, 90.77% and 100% respectively).

Besides, after review of the error – related sample points in the results of classified mapping, it is discovered that some of the sample points are located at the boundary of two different land types (because random sample points on a 20 × 20 regular grid are adopted in the paper) and therefore they are difficult to be classified. Therefore, if the errors caused by visual interpretation can be eliminated, the precision of classified mapping can be higher than that listed in Tab. 2 ~ 5.

For efficiency of classified mapping, with two groups of experimental data as examples, the efficiency of the KTLC method and the EC method is shown in Tab. 6 under the conditions ofIntel Core i7 2.4 GHz, 4 GB memory and Windows 7 environment. It can be discovered that the KTLC method saves much time in obtaining object samples on the premise of ensuring high precision, so its efficiency is greatly improved when compared with the EC method.

Tab. 6 Comparison of efficiency based on two methods

Methods	Consumption time of exprimental image 1/h	Consumption time of exprimental image 2/h
KTLC	0.5	0.7
EC	1.2	1.

4 Conclusion

A method for rapid classified mapping of land use information on high-resolution remote sensing images is studied in the knowledge transfer mechanism. Compared with the extensively used methods for classified mapping with the software eCognition, the KTLC method proposed effectively combines machine learning, knowledge accumulation and agricultural remote sensing field. In addition to providing classification results comparable with those of the EC method, the KTLC method also improves efficiency greatly, thus improving the automation level of classified mapping of land use information. It has great application prospect to fully explore the relationship between the historical data and current data. The studies provide new ideas for quick collection of land use information in key areas in respect of agricultural remote sensing field.

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基于低空遥感与迁移学习的土地利用信息快速制图方法

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摘要：为解决样本的手工获取和常规的目视解译难以适应目前农业土地资源信息自动化提取的需求问题，引入时空数据挖掘技术，运用关联知识迁移学习机制，提出了一种基于知识迁移学习的高分辨遥感影像土地利用信息分类制图方法（KTLC）。首先，运用改进的均值漂移算法对新的待分类制图影像进行分割获得影像对象，然后，将分割后对象的矢量边界与前时相土地利用矢量专题图进行配准、嵌套，通过叠加分析获取当前影像中的不变对象，并通过光谱、空间信息阈值筛选完成不变对象的提纯，进而将历史专题图中的地物类别知识迁移到新影像对象上，建立新的特征与地物类别映射关系，最后，运用决策树构建分类规则完成当前影像的快速分类制图，并将所提方法与利用易康（eCognition）软件进行分类（EC）的结果进行对比。研究结果表明，对于 2 组实验影像，KTLC 方法分类总体精度分别为 88.61%、88.30%，EC 方法分类的总体精度分别为 89.87%、84.84%，2 种方法分类制图精度相当，但在效率方面，KTLC 方法优于 EC 方法。

关键词：低空遥感技术；土地利用信息；分类制图；不变对象获取；知识迁移学习；先验知识

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Landuse Information Quick Mapping Based on Low Altitude Remote Sensing Technology and Transfer Learning

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Abstract: Obtaining surface spatio-temporal data rapidly, automatically and accurately is an important issue in agriculture informationization and intellectualization. Samples obtained by manual and conventional manual visual interpretation are difficult to adapt the demands of current agricultural land resources information automatic extraction. At the same time, low altitude remote sensing technology as a kind of emerging technology for earth observation in recent years, with its flexibility, high efficiency, low cost, was widely used in the investigation of all kinds of resources. If only extraction information from single phase image, regardless of the historical image data set information extraction has been completed, it will cause information waste and repeated work. Based on this, spatio-temporal data mining technology was introduced, and related knowledge transfer learning mechanism was used, a novel landuse information classification method based on knowledge transfer learning (KTLC) was proposed. Firstly, new image was segmented by improved mean shift algorithm to obtain image objects. Secondly, the vector

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boundary of the objects and former historical landuse thematic map were matched and nested, invariant objects were obtained through overlay analysis, and purification of invariant object was finished by spectral and spatial information threshold filtering. The historical features category knowledge of thematic map was transferred to the new image objects. Finally, current images classification mapping was completed based on decision tree, and landuse classification mapping results were completed by the KTLC and eCognition for landuse information mapping classification (EC). The experimental results showed that KTLC could obtain accuracies equivalent to EC, and also outperforms EC in terms of efficiency.

Key words: low altitude remote sensing technology; landuse information; classification mapping; invariant objects acquisition; knowledge transfer learning; prior knowledge

引言

快速、准确地获取地表时空数据是农业信息化、智能化面临的重要问题。通常情况下，农业信息本底调查（如基本农田面积监测、农作物种植结构调查等）时选取的数据源都是卫星影像[1-5]。然而，卫星传感器受天气制约，在多云雾地区（如四川盆地）很难连续获取需求的影像数据，卫星影像普遍空间分辨率较低，对于精细的农业用地监测，尤其是分散、不连续的小块耕地很难被识别[6-7]。同时，当前的土地利用信息获取与更新方式仍然是通过大量的人工解译，工作量大、效率偏低，即使有学者提出过自动解译方法，也需要大量的手动采集样本，远未达到真正的自动化。这就对数据源的分辨率和信息提取技术提出了更高的要求。在此形势下，以无人机为代表的低空遥感技术应运而生。无人机相较于传统的航空摄影飞机有以下优势：可快速起降、重复作业；影像采集成本低；获取的影像空间分辨率高[8-10]。无人机低空遥感技术通过提供低成本、厘米级分辨率影像，在土地利用信息数据需求精度高的基本农田保护区有着巨大的应用潜力。

随着遥感技术的飞速发展，获得的遥感影像空间分辨率越来越高。通过低空遥感技术获取的高分辨率影像上，地物的光谱信息更加丰富，同类地物内的光谱差异增大，不同地类的光谱差异减少，同物异谱及同谱异物现象更加普遍。影像中大量细节的出现和地物光谱特征的复杂化导致以传统光谱统计特征进行分类的方法，如极大似然法、最小距离法、K-均值聚类法等分类精度降低[11]。BAATZ 等[12]根据高分辨率遥感影像的特点，提出了面向对象的遥感影像分类方法，随着高空间分辨率影像的逐渐普及，面向对象的分析方法正在逐渐取代传统的基于像素的分析方法[13]。对象化技术可以有效提取光谱、形状以及纹理信息，同时可进一步地融合层次关系或语义信息，更符合人类视觉对影像进行目视解译的原理与过程[14-15]。当前诸多研究[16-18]都证明面向对象的分类方法在改进高分辨率遥感影像自动提取方面有着巨大的潜力，是高分辨率影像自动分类的理想选择。

目前解决知识迁移的方法可归纳为 4 类，即：实例迁移、特征迁移、参数迁移和关联知识迁移[19-20]。本文在关联知识迁移支持下，针对通过低空遥感技术获取高分辨率影像分类制图任务，设计基于不变对象检测的地物类别标签（关联知识）的迁移方法。通过新影像和前时相土地利用矢量专题图配准、嵌套，获取新影像上的不变地物，并将前时相解译的地物类别标签知识迁移至新影像，从而实现“不变地物类别解译知识”从源领域向目标领域的迁移，用于建立新的特征-地物映射关系，实现一种高分辨遥感影像土地利用信息的分类制图方法。

1　研究区及数据概况

研究区位于四川省德阳市广汉市连山镇基本农田保护区。广汉市境内土壤的成土母质为基岩风化物和松散堆积物 2 类。土层厚度大于 100 cm 的面积占总耕地面积的 7.43%，小于 30 cm 的面积仅占总耕地面积的 1.5%。大部分土壤可耕性好、适耕期长、宜种范围广、保肥供肥性能较好。但广汉市人多地少，面积 548 km^2，总人口 60 万，但耕地面积只有 3.4 万 hm^2，耕地保有量 3.1 hm^2，基本农田保护数 2.8 万 hm^2。根据国家土地利用分类标准并结合当地实际情况，研究区包含的主要土地利用类型有：耕地、林地、住宅用地、道路、水体、其他土地 6 大类。研究区位置示意图如图 1 所示。

考虑到研究区地形起伏不大，方便起降，实验选用了弹射式固定翼无人机，飞行平台上搭载了 Canon EOS 5D Mark II 数码相机，预设的航向重叠度和旁向重叠度分别为 75% 和 45%。飞行航高为 600 m，相机焦距为 24.49 mm。获取的无人机影像空间分辨率达到 0.2 m。研究区前时相历史土地利用专题图制图时间为 2014 年 6 月，如图 2a、2b 所示。无人机航拍时间为 2015 年 7 月，为了更好地验

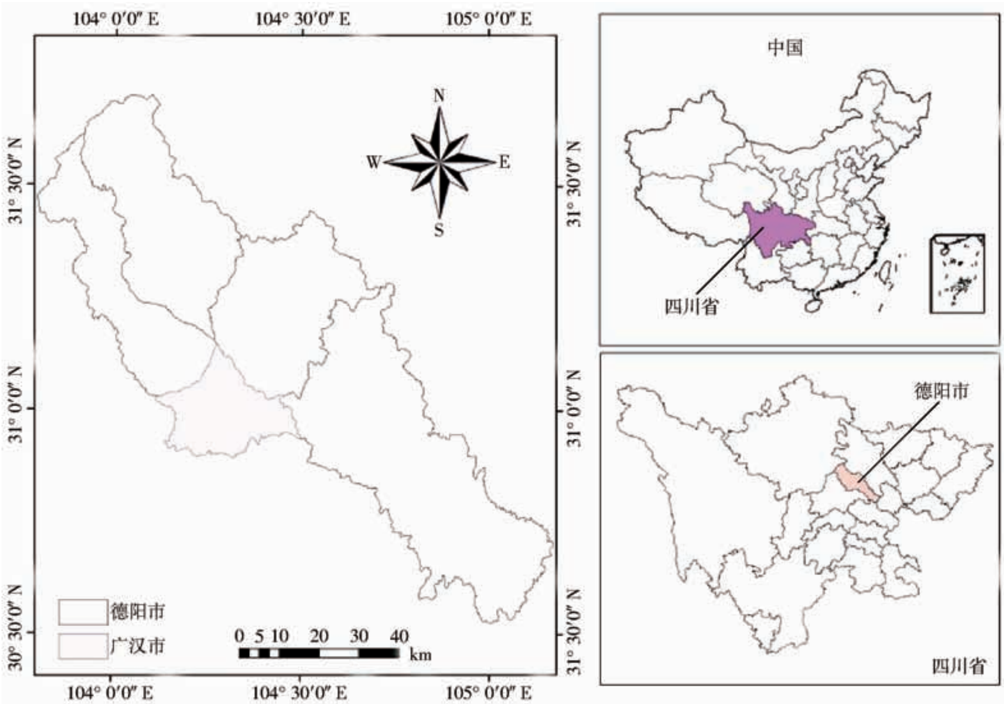

图1　研究区位置

Fig. 1　Location of Guanghan city selected for experimental purpose

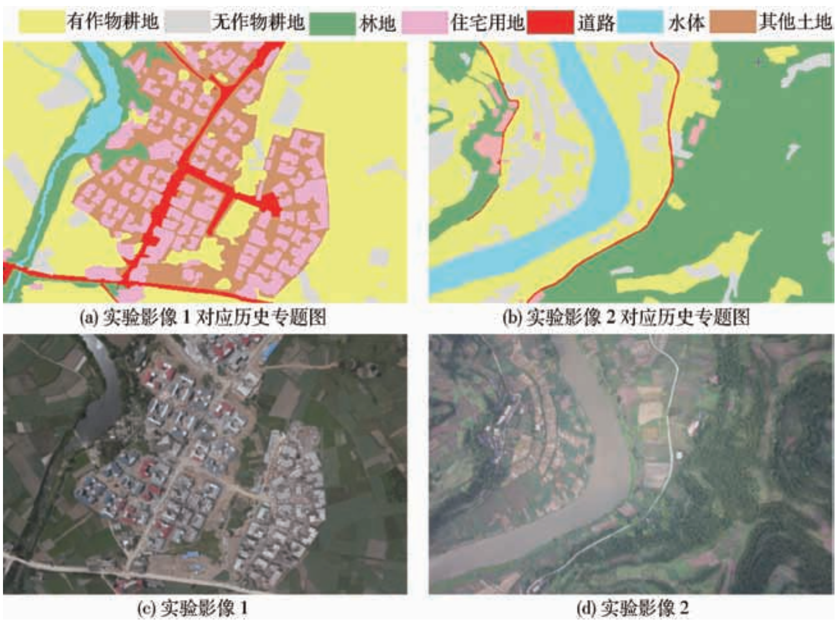

图2　历史土地利用专题图和当前实验无人机影像

Fig. 2　Preliminary thematic landuse maps and experimental UAV images

证方法的有效性和适用性，本文选取了2种典型的不同地类混合无人机影像，第1种为“复杂建筑物-耕地”混合影像，如图2c所示；第2种为“林地-耕地”混合影像，如图2d所示。

2　工作流程与研究方法

2.1　工作流程

对获取的原始无人机影像进行匀色、匀光、生成正射影像等预处理。预处理完成后，首先，运用改进的均值漂移算法对待分类制图影像进行多尺度分割获得影像对象，然后，将分割对象的矢量边界与前时相土地利用专题图进行配准、嵌套，通过叠加分析获取当前影像中的不变对象，进而通过光谱、空间信息阈值筛选剔除错误的不变对象，最后，将不变地物对象的类别通过迁移学习转移到当前目标影像，运用决策树构建分类规则完成当前影像的快速分类制图，并与直接利用面向对象分类软件易康(eCognition)分类制图结果进行对比。

2.2　影像数据预处理

无人机搭载的相机属于非量测型数码相机，拍

摄的影像存在较严重的镜头畸变，因此需要根据相机的畸变参数对影像进行畸变差校正[21-22]。又由于飞行过程中曝光时间间隔、天气差异会导致影像色彩存在色差，故采用掩膜方法对影像进行匀色、匀光处理。通过飞行控制系统记录的飞机姿态参数数据，对影像初步排序定位进行相邻像对同名点匹配。在完成同名点匹配后，根据共线方程条件进行区域网平差。区域网平差完成后，将地面控制点坐标信息加入，完成绝对定向，进而获取校正后的正射影像，为后续土地利用信息快速更新制图提供了高精度的正射影像数据。

2.3　基于迁移学习的土地利用信息制图(KTLC)方法

2.3.1　改进的均值漂移分割与对象图谱特征计算

首先，将预处理后的无人机影像划分为纹理区和均色区。均色区直接利用均值漂移算法获得；纹理区则利用归一化分布密度获取合适的带宽，再使用均值漂移算法进行分割。然后，通过构造代价函数判别相邻区域是否需要合并，以消除过分割区域。本文所采用的改进均值漂移分割算法可参见文献[23]。然后，将分割对象的矢量边界与前时相土地利用专题图进行配准、嵌套，使两者在一致的空间参考下。进而通过叠加分析获取当前影像中的不变对象。完成影像分割后，为保证后续的分类工作顺利开展，需要计算对象的特征。本文综合考虑光谱、形状、纹理 3 类特征，计算了表 1 所列的 18 个特征。

2.3.2　不变对象样本提纯

需要说明的是，通过叠加分析获取当前影像中的不变对象可能存在错误。为此，需要设计规则来剔除错误的不变对象。本文综合考虑光谱和空间信息来提纯不变对象，具体方法为：计算对象中像元亮度均值与类型亮度值中心(均值)的距离(差值)来进行对象提纯判断，即

表 1　对象图谱特征

Tab. 1　Spatial and spectral features of objects

光谱特征			形状特征			纹理特征		
特征名	图谱类型	注释	特征名	图谱类型	注释	特征名	图谱类型	注释
R_Mean	谱	红光波段均值	L/W	图	长宽比	GLCM_H	图	同质性
G_ Mean	谱	绿光波段均值	Geo_L	图	对象长度	GLCM_E	图	熵
B_ Mean	谱	蓝光波段均值	Geo_W	图	对象宽度	GLCM_C	图	对比度
R_Dev	谱	红光波段标准差	Border_L	图	对象边长	GLCM_V	图	方差
G_ Dev	谱	绿光波段标准差	Compact	图	紧致度	GLCM_D	图	异质性
B_ Dev	谱	蓝光波段标准差	Num_P	图	像素数目	GLCM_A	图	角二阶矩

$$\begin{cases} \| R_{x_i} - M_{\mu_i} \| \leqslant 4\delta_i \\ \| G_{x_i} - M_{\mu_i} \| \leqslant 4\delta_i \\ \| B_{x_i} - M_{\mu_i} \| \leqslant 4\delta_i \end{cases} \tag{1}$$

式中　R_{x_i}、G_{x_i}、B_{x_i}——对象在红、绿、蓝 3 个波段中的亮度

M_{μ_i}——对象样本亮度值均值

δ_i——每一个对象内部像元光谱标准差

从空间信息来看，可根据每一个对象内部像元光谱标准差是否超限来判别是否为错误对象，即

$$\begin{cases} \delta_i \leqslant 0.2R_{b_{\max}} \\ \delta_i \leqslant 0.2G_{b_{\max}} \\ \delta_i \leqslant 0.2B_{b_{\max}} \end{cases} \tag{2}$$

式中　$R_{b_{\max}}$、$G_{b_{\max}}$、$B_{b_{\max}}$——影像在红、绿、蓝 3 个波段所能达到的最大亮度

如果所选择的不变对象同时满足式(1)、(2)，则为可靠不变对象，否则为不可靠不变对象，应剔除。

2.3.3　关联知识迁移学习与快速分类制图

在获取并提纯了当前目标影像对象样本后，根据对象已计算的图谱特征，选择最佳的特征组合和分类模型进行监督分类。有关特征优化选取、分类模型的方法较多，为简化，同时兼顾效率，本文采用决策树算法完成特征的优选及分类模型的训练，从而构建判别规则集用于分类，进而完成当前影像的分类制图。

2.4　EC 方法

为了验证所提方法可靠性，利用广泛应用的易康软件(eCognition 8)进行土地利用分类制图实验，与 KTLC 方法进行对比。首先需要进行影像分割，然后对分割后的影像对象进行分类制图。考虑到标准最邻近法操作简单、高效，适用范围广，本文 EC 方法采取标准最邻近分类制图。具体流程如下：首先，选定样本对象，对样本进行统计分析，从而得到如纹理、光谱、形状以及邻域信息等相关的特征值，构建多维特征空间；然后，计算需要分类对象和样本之间的距离差值，依据特征的距离关系，借助隶属度函数，判断待分类对象同哪个样本类距离最近，则将该对象分到该类别中。

3　结果与分析

3.1　快速分类制图

根据 2.1 节所述原理,设定改进均值漂移分割的光谱尺度参数为 7、空间尺度参数为 10,采用改进均值漂移算法分割结果如图 3 所示。

将分割对象的矢量边界与 2014 年 6 月获得的历史土地利用专题图进行配准、嵌套,通过叠加分析获取当前影像中的不变对象,并根据光谱和空间信息完成不变对象的提纯,删除误提取的不变对象,进而通过知识迁移学习将不变地物对象的类别通过迁移学习转移到当前目标影像。最后利用决策树对不变对象样本的图谱特征进行优化选择,构建分类规则进行土地利用信息的分类制图。最终,KTLC 方法分类制图结果如图 4a、4b 所示。

根据 2.3 节所述原理,本文实验过程中分割参数设置如下:分割尺度参数设置为 90,颜色/形状参数设置为 0.5/0.5,光滑度/紧凑度参数设置为 0.5/0.5。最终通过 EC 方法得到土地利用分类制图结果如图 4c、4d 所示。

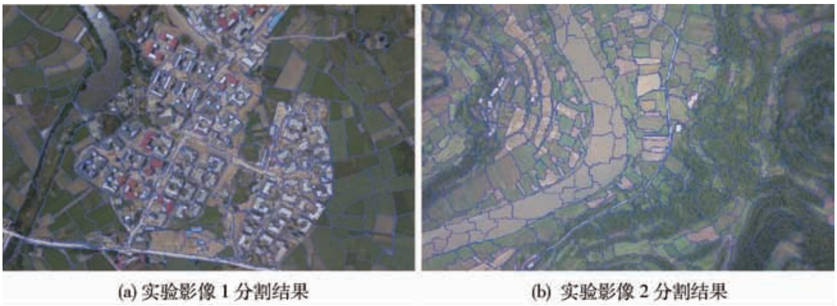

图 3　改进均值漂移算法分割结果

Fig. 3　Segmentation results based on improved mean shift method

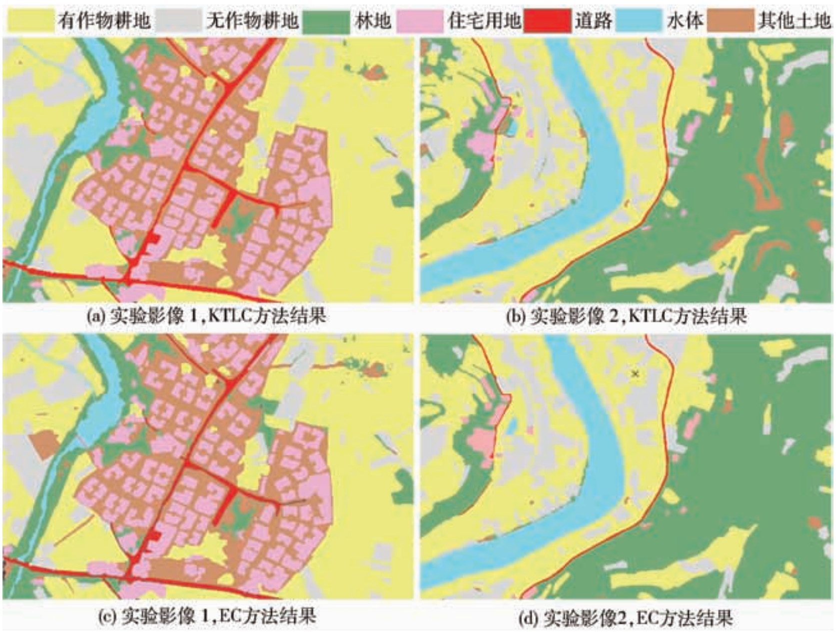

图 4　2 种方法分类制图结果

Fig. 4　Results of classification mapping based on two methods

3.2　精度与效率评价

通常,分类结果的精度评价有定性评价和定量评价两种方式。定性评价主要比较分类后的图斑边界与实际地物的吻合程度,该方法有较强的主观性;定量评价则是通过计算总体精度、Kappa 系数等进行评价[23-24]。由于无人机影像空间分辨率很高,可直接通过人工目视解译获得验证数据。为使评价结果客观性更强,本文采用如下方法获得验证点:首先绘制与实验影像面积相同的 20×20 规则网格,然后在每个网格中随机生成 10 个随机点,最后通过目视解译获得每个随机验证点的土地利用类型。对于实验影像 1,获取了 395 个有效验证点;对于实验影像 2,获取了 382 个有效验证点。通过将验证点与分类结果进行叠加来判断分类制图结果是否正确。经过计算可得,对于实验影像 1,KTLC 方法分类的总体精度为 88.61%,Kappa 系数为 0.86;EC 方法分类的总体精度为 89.87%,Kappa 系数为 0.87,具体结果如表 2、3 所示。对于实验影像 2,KTLC 方法分类

的总体精度为 88.30%，Kappa 系数为 0.82；EC 方法分类的总体精度为 84.84%，Kappa 系数为 0.79，具体结果如表 4、5 所示。

实验影像 1 为“复杂建筑物-耕地”混合影像，观察表 2、3 可发现，KTLC 方法和 EC 方法在建筑用地、有作物耕地和无作物耕地三者类别区分精度较高，说明在该类高空间分辨率影像上建筑用地、有作物耕地和无作物耕地具有较强的可分性。采用 KTLC 方法林地分类精度为 74.14%、道路分类精度为 69.23%，这 2 种地类的分类精度低于采用 EC 方法，但由于没有分类精度特别低的地类且有作物耕地、建筑用地、水体的分类精度较高，分别为 98.15%、94.25%、100%，使得 KTLC 方法的总体精度达到 88.61%，与 EC 方法的总体精度 89.87% 基本相当。实验影像 2 为“林地-耕地”混合影像，观察表 4、5 可发现，KTLC 方法和 EC 方法均在林地和有作物耕地的区分上出现较多分类错误，原因在于林地和有作物耕地在光谱和纹理上相似性较高，若

表 2　实验影像 1 精度混淆矩阵(KTLC 方法)

Tab.2　Confusion matrix of accuracy for experimental image 1 (KTLC method)

	林地	有作物耕地	无作物耕地	道路	建筑用地	裸地	水体
林地	43	12	1	0	2	0	0
有作物耕地	2	106	0	0	0	0	0
无作物耕地	0	4	36	0	1	2	0
道路	0	0	0	18	5	3	0
建筑用地	0	0	0	2	82	3	0
裸地	2	0	5	1	0	53	0
水体	0	0	0	0	0	0	12
生产精度/%	91.49	86.89	85.71	85.71	91.11	86.89	100
用户精度/%	74.14	98.15	83.72	69.23	94.25	86.89	100
总体精度为 88.61%　Kappa 系数为 0.86							

表 3　实验影像 1 精度混淆矩阵(EC 方法)

Tab.3　Confusion matrix of accuracy for experimental image 1 (EC method)

	林地	有作物耕地	无作物耕地	道路	建筑用地	裸地	水体
林地	46	6	0	0	0	0	0
有作物耕地	3	101	0	0	0	0	0
无作物耕地	0	4	30	0	0	4	0
道路	0	0	0	14	4	2	0
建筑用地	1	0	1	3	90	4	0
裸地	1	0	6	0	0	63	1
水体	0	0	0	0	0	0	11
生产精度/%	90.20	90.99	81.08	82.35	95.74	86.30	91.67
用户精度/%	88.46	97.12	78.95	70.00	90.91	88.73	100
总体精度为 89.87%　Kappa 系数为 0.87							

表 4　实验影像 2 精度混淆矩阵(KTLC 方法)

Tab.4　Confusion matrix of accuracy for experimental image 2 (KTLC method)

	林地	有作物耕地	无作物耕地	道路	建筑用地	裸地	水体
林地	137	11	0	0	1	0	0
有作物耕地	15	82	2	0	0	0	0
无作物耕地	0	4	59	0	0	2	0
道路	0	0	0	11	2	0	0
建筑用地	2	0	0	2	15	1	0
裸地	1	0	6	0	1	12	0
水体	0	0	0	0	0	0	16
生产精度/%	88.39	84.54	88.06	84.62	78.95	80.00	100
用户精度/%	91.95	82.83	90.77	84.62	75.00	60.00	100
总体精度为 88.30%　Kappa 系数为 0.82							

表 5　实验影像 2 精度混淆矩阵（EC 方法）

Tab. 5　Confusion matrix of accuracy for experimental image 2 (EC method)

EC 方法	林地	有作物耕地	无作物耕地	道路	建筑用地	裸地	水体
林地	141	10	2	0	0	1	0
有作物耕地	20	74	0	0	0	0	0
无作物耕地	0	1	51	0	1	2	0
道路	0	0	0	8	4	1	0
建筑用地	1	0	0	1	16	2	0
裸地	4	0	7	1	0	14	0
水体	0	0	0	0	0	0	15
生产精度/%	84.94	87.06	85.00	80.00	80.00	70.00	100
用户精度/%	91.56	78.72	92.73	61.54	80.00	53.85	100
总体精度为 84.84%　Kappa 系数为 0.79							

能在迁移学习过程中增加可靠样本数量会使精度提高。KTLC 方法的总体精度为 88.30%，略高于 EC 方法的 84.84%，特别是对于林地、无作物耕地、水体的提取精度较高，分别达到了 91.95%、90.77% 和 100%。

此外，核查分类制图结果出现错误的样本点发现，由于本文采用的是根据 20×20 规则网格中随机生成的样本点，因此有部分样本点处于两类不同地类的交界线上，难以准确划分其类别。所以，若能排除目视解译所致错误结果，分类制图精度应高于表 2～5 计算结果。

在分类制图效率方面，以本文 2 组实验数据为例，在 Intel Core i7 2.4 GHz，4 GB 内存、Windows 7 环境下，KTLC 方法和 EC 方法效率如表 6 所示。可以看出，KTLC 方法在保证精度的前提下，在对象样本获取上节省了大量时间，效率较 EC 方法有较大提升。

表 6　2 种方法效率对比

Tab. 6　Comparison of efficiency based on two methods

方法	实验影像 1 耗时/h	实验影像 2 耗时/h
KTLC	0.5	0.7
EC	1.2	1.3

4　结束语

研究了一种知识迁移机制下的高分辨遥感影像土地利用信息快速分类制图方法。与当前广泛应用的分类软件（eCognition）分类制图方法进行对比，本文所提方法（KTLC）有效地将机器学习、知识发现与农业遥感领域相结合，分类结果不仅与 EC 方法结果相当，而且在效率上有较大提升，提高了土地利用信息分类制图的自动化程度。充分发掘历史数据与当前数据的关联关系有较大的应用前景，本文研究为农业遥感中重点区域的土地利用信息快速获取提供了新思路。

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