Application of image convolution to extract the urban extent

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Abstract: With a convolution algorithm, urban land use proportions were calculated based on remote sensing classification data, which were used as thresholds to distinguish between urban and non-urban area, and then urban extent was extracted. Indexes system was proposed to determine the size of the convolution template and the threshold by evaluating extraction results. We took Beijing as a study area and validated the feasibility of the method by using classification data of SPOT 5 multi-spectral images. Combining with the built-up area of statistical data, 504 combinations of template and threshold were used to do the extraction test and the effects of templates and thresholds on the extraction results were discussed. Finally, combination of (205, 51) was selected to extract the urban extent. The result showed that: (1) this method solved the problem that urban land acquired from remote sensing monitoring differed from urban extent that geographical studies cared about and provided a new way to prepare the basic data for urban study. (2) Test result indicated that both the lower or higher threshold will exaggerate or understate the extracted result, and that a small size of template cannot eliminate the random error meanwhile a large size would lead the result being too smooth. (3) For the classification data of SPOT 5 multi-spectral image, the extraction results were the best while the size of the template ranges from 193 to 205 (around 4 km^2) and the threshold is around 50.

Key words: urban extent extraction, remote sensing monitoring, convolution algorithm, urban land use proportion, Beijing

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1 INTRODUCTION

As population grows rapidly and urbanization processes, studies on urban morphology, sprawl pattern, dynamic models and spatial structures have become the present focuses within the domain of geography (Mu, *et al*., 2007). The determination of urban extent is the basis of such studies. Remote sensing is a significant data source for the study of urban phenomena (Longley, 2002). Remote sensing is quick, accurate tool and can be used periodically to monitor the dynamic characteristics of urban area and provides multi-temporal images for urban study. At the same time, image processing and information extraction technology have been developed and perfected, providing further technical support to remote sensing monitoring, which is now one of the main methods in urban monitoring researches.

Research of urban areas using remote sensing monitoring is primarily carried out through the extraction of urban land. Urban land acquired from remote sensing monitoring is a land cover type. It is the buildings distribution area of urban land cover which is acquired based on spectral properties of buildings. Usually, it is considered as urban extent in urban study. According to remote sensing spectral features, urban land is extracted through visual image interpretation, classification of remote sensing images or information extraction using remote sensing indices, *etc*. For instance, urban land is delineated directly by screen digitization through visual image interpretation (Mu, *et al*., 2007; Wang, *et al*., 2007), urban land is obtained through classification of remote sensing images (Jacquin, *et al*., 2008; Taubenbock, *et al*., 2009; Bhatta, *et al*., 2010), based on several spectral indices and index models, urban land is extracted from images (Zha, *et al*., 2003; Li, *et al*., 2008; Li, *et al*., 2009).

An urban area is an inhabited settlement dominated by a non-agricultural population with a certain population size, which has regional and general characteristics (Xu, *et al*., 1997). In the study of urban geography, the density of urban population is a main index to determine urban extent. Meanwhile, urban functions and urban facilities (*i.e*., the supply of water, electricity, square, Greenland, parks, museums, *etc*.) are also used as an urban delimitation basis. The determination of urban extent is thus decided according to the characteristics of land use. Urban land acquired from remote sensing monitoring differs from urban extent that

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geographical studies care about, which refers to a land cover type. It is the distribution areas of buildings including the land uses of residential area, industrial land, warehouse and mining land, traffic land and construction land, which can be measured at the scale of remote sensing. Urban extent is a continuous distribution area of the city entity geospatially. It includes many types of land covers apart from building land, such as vegetation, water, *etc*. Urban land acquired from remote sensing with higher density is the core area of city, and it differs from urban extent either in amount or in geographical space.

To solve the above-mentioned problem and transform the achievements of remote sensing monitoring into the basic data for urban study, this paper provides a method to extract urban extent using urban land use proportion, which is a quantified index of urban land using remote sensing monitoring. We used Beijing as a study case and verified the feasibility of the method based on the classification of remotely sensed data in 2007.

2 METHOD OF EXTRACTION

According to the comprehensive characteristics of the determination of urban extent, the density of urban buildings reaching a certain proportion can be used as the dividing criterion of urban extent (Zhang, *et al*., 1999). Through convolution operation, urban discrimination, clumping, *etc*., extraction of urban extent was performed. The detailed process is described as follows. First of all, the urban land use proportion was calculated by convolution operation based on classification of remote sensing images. Then, we used the urban land use proportion as the thresholds to distinguish urban area from non-urban area. Lastly, urban extent was extracted from the result of discrimination by use of clumping. The detailed procedure is shown as Fig. 1.

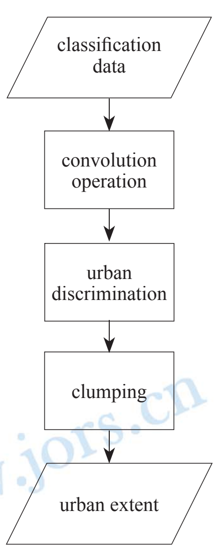

Fig. 1 The flow chart of the urban extent extraction

2.1 Calculation of urban land use proportion

The urban land use proportion was obtained through image convolution operation (Zhang, *et al*., 1999). Convolution operation is an algorithm to carry out neighborhood detection on the image in a spatial domain. It is a common method adopted in image processing, which can be used in image smoothing, signal processing and conversion, differentiation and edge detection. It is implemented through a selected convolution function which is also called template composed of a small two-dimensional image with size of $M\times N$. The algorithm is listed in detail as follows (Tang, *et al*., 2004).

Choose a template $\varphi(m, n)$ with size of $M\times N$, and start the operation at the top left corner of the image. Firstly, open a same size moving window $f(m, n)$ on the image. Secondly, get the accumulated value of all elements of the entrywise product of $\varphi(m, n)$ and $f(m, n)$. Thirdly, set the calculation result $g(i, j)$ as the pixel value of the central pixel of window $f(m, n)$. The formula of the template operation is shown as below.

$$g(i,j)=\sum_{m=1}^{M}\sum_{n=1}^{N} f(m,n)\varphi(m,n) \tag{1}$$

After that, move the template one column to the right along the same row and shift the window correspondingly to calculate $g(i, j)$ as Eq. (1), which then is used as the central pixel value of the new window. Based on this analogy, scan the whole image row by row and column by column, and then produce a new image with calculation result as the pixel value. Usually, the size of template for convolution operation is an odd number, and M equals N, because that the window demands a central pixel.

In this research, when we calculate the urban land use proportion, we use a mean smoothing template for convolution function, *i.e*., $\varphi(m, n)=1$. It can be calculated by

$$\begin{cases} g(i,j)=\dfrac{1}{N^2}\displaystyle\sum_{m=1}^{N}\sum_{n=1}^{N} f(m,n)\times 100 \\ f(m,n)=\begin{cases}1, & \text{Urban}\\ 0, & \text{Nonurban}\end{cases}\end{cases} \tag{2}$$

where $f(m, n)$ is the classification of remote sensing image. If the land use type is urban, $f(m, n)$ equals to 1; if the land use type is nonurban, $f(m, n)$ equals to 0. The value of $g(i, j)$ ranges from 0 to 100, which represents urban land use proportion in percent.

2.2 Discrimination and extraction

Perform urban discrimination by judging the result $g(i, j)$ of Eq. (2): set a threshold t, according to Eq. (3), calculate and produce a new image $G(i, j)$.

$$G(i,j)=\begin{cases}0, & g(i,j)\in[0,\ t]\\ 1, & g(i,j)\in(t,\ 100]\end{cases} \tag{3}$$

The discrimination result $G(i, j)$ contains both urban extent and residential regions, which distribute independently around the city or in suburban counties and townships with a certain area. Do clumping to $G(i, j)$, and extract the outer boundary of the biggest patch of clumping result as urban extent, thus to eliminate the impact of those residential regions on the extraction result.

2.3 Determination of template and threshold

During the process of urban extent extraction, two most important factors are the size of template for convolution operation (henceforth abbreviated as template) and the threshold of urban land use proportion for urban discrimination (henceforth abbreviated as template). A lower threshold will exaggerate the urban extent, while higher values will understate it. The selection of the template is relevant to the spatial structure and magnitude of urban and nonurban patches. A lower size of template cannot eliminate the influence of random variation. In contrast, a higher template will result in lower value of urban land use proportion (Zhang, *et al*., 1999).

We determined the best combination of template and threshold by analyzing the impacts of template and threshold on area accuracy of extraction result. Two sets were established: template set $\boldsymbol{K}$ and threshold set $\boldsymbol{T}$. Set $\boldsymbol{K}$ comprise templates with identifier $\boldsymbol{K}_x$, $x = 1, 2, \cdots, a$. Set $\boldsymbol{T}$ include thresholds with serial number $\boldsymbol{T}_y$, $y = 1, 2, \cdots, b$. Assembling the element of those two sets and extracting urban extent with each combination, the sum of a and b multiplied together will produce extraction results.

We adopted two indexes to assess the relative accuracy of the extraction result: mean accuracy and standard deviation of mean accuracy, two indexes to evaluate the absolute error of the extraction result: root-mean-square error and deviation. We set the extraction result area of combination ($\boldsymbol{K}_x$, $\boldsymbol{T}_y$) as A_{xy}, and the real area of urban extent is denoted as A_0. Various indexes are defined as follows.

2.3.1 Mean accuracy

P_{xy} represents the accuracy of extraction when the template $\boldsymbol{K}_x$ and threshold $\boldsymbol{T}_y$ are used:

$$P_{xy} = \left[1 - \frac{|A_{xy} - A_0|}{A_0}\right] \times 100\% \tag{4}$$

$\overline{P_x}$ represents the accuracy of extraction when the template is $\boldsymbol{K}_x$:

$$\overline{P_x} = \sum_{y=1}^{b} P_{xy} / b \tag{5}$$

$\overline{P_y}$ represents the accuracy of extraction when the threshold is $\boldsymbol{T}_y$:

$$\overline{P_y} = \sum_{x=1}^{a} P_{xy} / a \tag{6}$$

2.3.2 Standard deviation of mean accuracy

This reflects the fluctuation of the mean accuracy of the urban extent area extracted, namely, the discrete degree of the mean accuracy. $\overline{\delta_x}$ stands for the standard deviation of mean accuracy of urban extent extracted while the template is $\boldsymbol{K}_x$.

$$\overline{\delta_x} = \frac{\sum_{y=1}^{b} \left|P_{xy} - \overline{P_x}\right|^2}{b} \tag{7}$$

$\overline{\delta_y}$ stands for the standard deviation of mean accuracy of urban extent extracted while the threshold is $\boldsymbol{T}_y$.

$$\overline{\delta_y} = \frac{\sum_{x=1}^{a} \left|P_{xy} - \overline{P_y}\right|^2}{a} \tag{8}$$

2.3.3 root-mean-square error and deviation

Both of these two parameters evaluate the average level of the degree of departure between areas of the extracted urban extent and the area of the real urban extent.

$RMSE_x$ and $bias_x$ denote respectively the root-mean-square error and deviation between areas of the extracted urban extent and the area of the real urban extent when the template is $\boldsymbol{K}_x$.

$$RMSE_x = \sqrt{\sum_{y=1}^{b} (A_{xy} - A_0)^2 / b} \tag{9}$$

$$bias_x = \sum_{y=1}^{b} (A_{xy} - A_0) / b \tag{10}$$

$RMSE_y$ and $bias_y$ denote respectively the root-mean-square error and deviation between areas of the extracted urban extent and the area of the real urban extent when the threshold is $\boldsymbol{T}_y$.

$$RMSE_y = \sqrt{\sum_{x=1}^{a} (A_{xy} - A_0)^2 / a} \tag{11}$$

$$bias_y = \sum_{x=1}^{a} (A_{xy} - A_0) / a \tag{12}$$

3 EXPERIMENT OF EXTRACTION

3.1 Study area and data

Beijing is located in the northern part of the north China plain, 39°26′N—41°04′N, 115°24′E—117°31′E. The land area of the whole municipality is 16140 km^2, and the plain area is about 6338 km^2 around 38.6% of the total area. Urban extent was within the pale of the 5th ring road in the plan. Along with increasing pace of urbanization in recent years, several areas in suburbs were added to urban districts. Being a political and cultural centre, hubs of industry have moved outward gradually. According to statistics, up to 2007, the built-up area of Beijing reached 1289.3 km^2, the resident population was up to 16.33 million, annual GDP for the entire area was 900.62 billion Yuan.

This research used classification data of SPOT 5 image for Beijing in 2007, which included 8 classes, namely forestland, grassland, orchard, farmland, vegetable plots, building land, unutilized land and water. Through an analysis of confusion matrix, the whole precision was 83.22% and the kappa coefficient was 0.8063. This data was produced by maximum likelihood classification (MLC) and an image mosaic of five scene SPOT 5 images, which covered the whole plain region and part of the mountainous area of Beijing. These five scene images are shown in Tabel 1.

Table 1 SPOT 5 images used in the study

Image ID	Orbit(K–J)	Acquisition time
1	279–268	2007-04-24
2	282–269	2007-05-03
3	282–270	2007-05-03
4	280–269	2007-05-19
5	280–270	2007-05-19

3.2 Sets of templates and thresholds

The template and threshold for urban extent extraction for Beijing in 2007 were as follows: in the range of 0—6 km^2, select a template every 0.25 km^2 resulting in 24 templates in total, choose the integer between 40 and 60 as the threshold, giving 21 thresholds in all.

Partial templates used in the experiment are listed in Table 2, where N represents the size of template shown by the pixels of the image, corresponding to the area of template. Because N must be an odd number, we chose the maximum odd number size template corresponding to the area with the template.

Table 2 Partial templates used for urban extraction

ID	Area /km^2	N
1	0.25	49
2	0.50	69
3	0.75	85
4	1.00	99
5	1.25	111

3.3 Result of extraction

Before extracting the urban extent, the classification data was recoded with the building land assigned a value of one and others a value of zero. Then, the urban-nonurban map of Beijing in 2007 was created.

Combining the 24 templates and 21 thresholds mentioned before, we then analyzed the selection of template and threshold. The analysis is discussed in detail in section 4. Finally, we selected (205, 51) as the template and threshold combination to extract urban extent which is shown in Fig. 2.

In 2007, the extracted Beijing urban extent is 1288.79 km^2. The scope of urban extent has reached or exceeded the 6th ring road, covered the whole urban districts and the most part of four suburb districts, namely Chaoyang, Haidian, Fengtai and Shijingshan, and reached out to some outer suburbs districts, namely Changping, Tongzhou, Daxing, Fangshan, Mentougou. There are some significant urban expansion axes along several major roads such as Jingtong expressway, national highway 102, 103 (east), Jingjintang expressway (southeast), Jingkai road, national highway 106 (south), national highway 107 (southwest), Jingyuan road, national highway 109 (west), and the Badaling Expressway (north). The SPOT 5 images of these corresponding regions were overlayed with urban extent, are shown in Fig. 3.

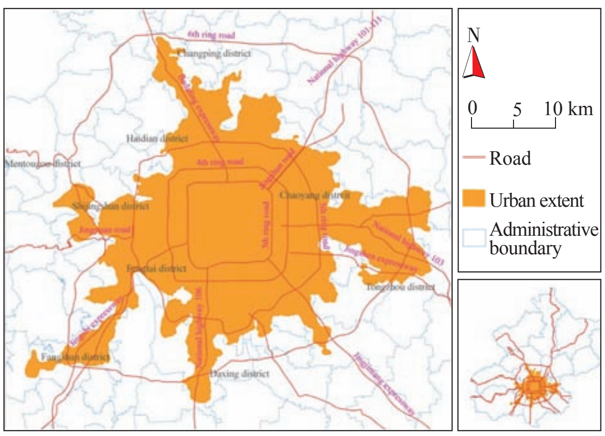

Fig. 2 Urban extent of Beijing in 2007

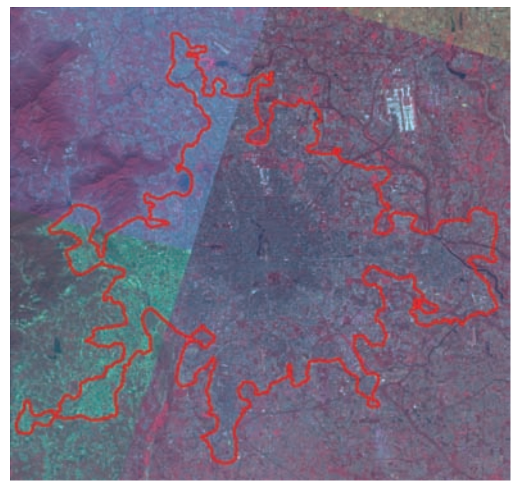

Fig. 3 Urban extent overlays with SPOT 5 images

4 SELECTIONS OF TEMPLATE AND THRESHOLD

The built-up area, as the most basic urban geographical concept, reflects the city as the region with a high concentration of population and various non-agricultural activities, which is different from the rural area, and can represent the urban landscape (Xu, *et al*., 1997). In China, the built-up area is used to character the urbanized area of a city by statistics department. Therefore, we use the built-up area as the real area of urban extent to discuss the selection of template and threshold in this paper.

4.1 Accuracy influenced by thresholds

Using the threshold $\boldsymbol{T}_y$, the mean accuracy, standard deviation of mean accuracy, root-mean-square error and deviation were shown in Fig. 4.

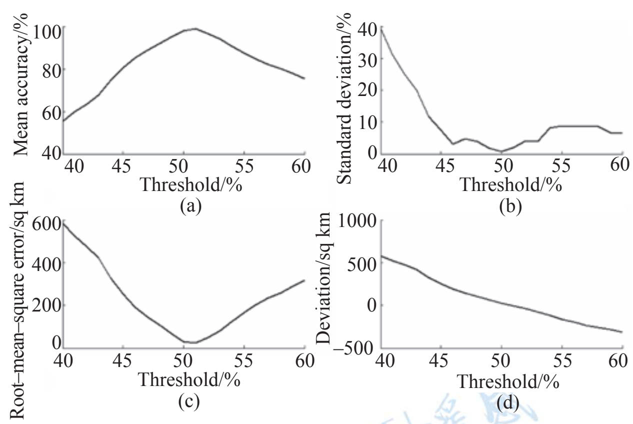

Fig. 4 Effects of threshold on accuracy of extraction
(a) Mean accuracy; (b) Standard deviation; (c) Root-mean-square error; (d) Deviation

It can be seen in Fig. 4 (a) that the mean accuracy increased first, and then decreased while the thresholds still increase. When the threshold was 51, the mean accuracy reached the maximum value. As shown in Fig. 4 (b), the standard deviation of mean accuracy presented the down trend as a whole, and fluctuated between partial thresholds. When the threshold was 50, the standard deviation of mean accuracy reached the minimum value. As the threshold was greater than 50, the standard deviation of mean accuracy showed an inconspicuous increase. With increasing threshold, the *RMSE* decreased first, and then increased. When the threshold was 51, a minimum *RMSE* value was observed (Fig. 4 (c)). Deviation decreased as the threshold increased and the absolute value of deviation showed the minimum value when the threshold was 51 (Fig. 4 (d)). Four indices clearly showed that the threshold will have great effects on accuracy of extraction and the highest accuracy was acquired at a threshold of 50.

4.2 Accuracy influenced by templates

With the template $\boldsymbol{K}_x$, the mean accuracy, standard deviation of mean accuracy, root-mean-square error and deviation were shown in Fig. 5.

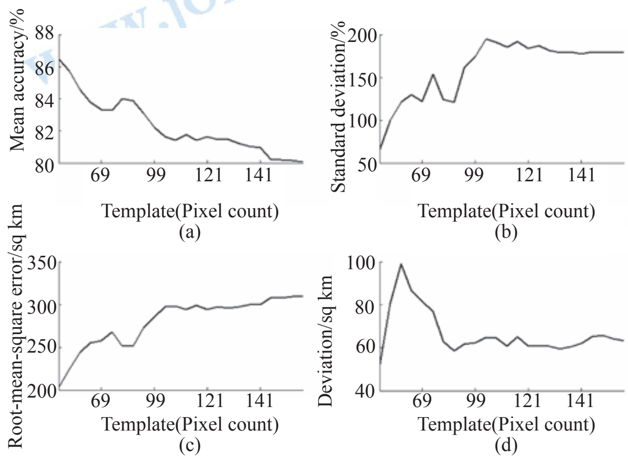

Fig. 5 Effects of template on accuracy of extraction
(a) Mean accuracy; (b) Standard deviation; (c) Root-mean-square error; (d) Deviation

It can be seen in Fig. 5 (a) that the mean accuracy generally presented a downward trend when the template size increased. As shown in Fig. 5 (b), the standard deviation presented an upward trend with the increase of template size. As the template size exceeded 165, the variation trend of standard deviation stabilized. With increasing template size, the *RMSE* will increase. Similarly, as the template size exceeded 165, the variation trend of *RMSE* became relatively stable (Fig. 5 (c)). With increasing template size, the deviation increased first, and then decreased. As the template size exceeded 149, the variation trend of deviation stabilized (Fig. 5 (d)).

The analysis result above showed that the template size will greatly influence the accuracy of extraction. When the template size increased, the mean accuracy decreased. When the template size ranged from 49 to 157, the standard deviation of mean accuracy, *RMSE* and deviation changed significantly. As the template size was greater than 157, three indexes changed to stable levels. This reported that a small template size will give random extraction results, while larger template, on the other hand, would lose some information of urban land use, even though it can eliminate the random error.

4.3 Best combination of template and threshold

Through the accuracy analysis we knew that, when the threshold was around 50, the extraction results were the best. The areas of extraction results of 50, 51, and 52 as the threshold were shown in Fig. 6. It can be seen from the graph that when the template size ranged from 193 to 205, only slight variation trend were acquired between the areas of three thresholds. According to the above analysis, we suggested that templates with the size within this range were most suitable. When the threshold was 51 and template size was 205, the extraction result had the highest accuracy, which was then selected (205, 51) as the best combination of template and threshold in this study.

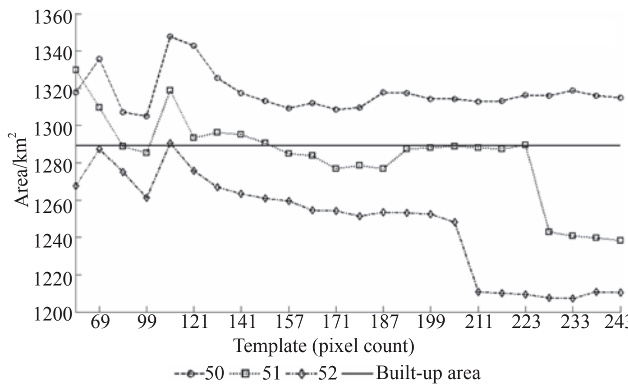

Fig. 6 Determination of template and threshold

5 CONCLUISON AND DISCUSSION

There is a great deal of difference between urban land resulting from remote sensing monitoring and urban extent. We designed a method to extract the urban extent from the remote sensing monitoring result in this study which was based on classification data of remote sensing images. By using of convolution operation, the urban land use proportion was calculated. Then, the area with urban land use proportion larger than a specific threshold was extracted as the urban extent. We used Beijing as a study case and extracted the urban extent of Beijing in 2007, by using the classification result of SPOT 5 images and statistical data of Beijing. The urban extent area for Beijing in 2007 determined by our method was 1288.97 km^2, which was only 0.51 km^2 less than the built-up area of Beijing in 2007. From the spatial distribution of the extracted urban extent, the urban boundary of Beijing exceeded the 5^{th} ring road, in some regions, the urban extent had gone beyond the 6^{th} ring road. Urban extent was distributed along major highways and national roads and formed visible urban growth axes.

During the process of urban extent extraction, the size of template and threshold were key problems. We proposed an accuracy assessment evaluation indicator system and chose 504 combinations of template and threshold to discuss the impacts of different templates and thresholds. The result showed that the threshold directly influenced the accuracy. If the threshold was lower or higher, the extracted result would be exaggerated or underestimated. When the threshold was around 50, extraction results were the best. The effect of the template size on the extraction accuracy was somewhat smaller. However, a small size of template cannot eliminate the random error while a large size of template would lead the result of the convolution being too smooth, and therefore affect the accuracy of urban extent. When the template size ranged from 193 to 205 (around 4 km^2), the extraction results were the best.

This study only performed the experiment of the extraction of urban extent based on the classification result of SPOT 5 images. For the other data sources, template size and threshold given by this study will be different and need further analysis. In addition, the method provided by this study is based on classification of remote sensing data, and thus the classification accuracy will impact on the result of extraction directly.

REFERENCES

Bhatta B, Saraswat S and Bandyopadhyay D. 2010. Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data. *Applied Geography*, **30**(1): 96–111 DOI: 10.1016/j.apgeog.2009.08.001

Jacquin A, Misakova L and Gay M. 2008. A hybrid object-based classification approach for mapping urban sprawl in periurban environment. *Landscape and Urban Planning*, **84**(2): 152–165 DOI: 10.1016/j.landurbplan.2007.07.006

Li J J, He L H, Dai J F, Li X C and Fu Q Y. 2008. Urban sprawl study based on impervious surface percent. *Remote Sensing Technology and Application*, **23**(4): 424–427

Li X R, Wang X L and Feng Z K. 2009. Research on urban expansion based on land use degree. *Progress in Geography*, **28**(3): 398–402

Longley P A. 2002. Geographical information systems: Will developments in urban remote sensing and GIS lead to 'better' urban geography? *Progress in Human Geography*, **26**(2): 231–239 DOI: 10.1191/0309132502ph366pr

Mu F Y, Zhang Z X, Chi Y B, Liu B, Zhou Q B, Wang C Y and Tan W B. 2007. Dynamic monitoring of built-up area in Beijing during 1973–2005 based on multi-original remote sensed images. *Journal of Remote Sensing*, **11**(2): 257–268

Tang G A, Zhang Y S, Liu Y M, Xie Y L, Yang X and Liu A L. 2004. Remote Sensing Digital Image Processing. Beijing: Publisher of Science

Taubenböck H, Wegmann M, Roth A, Mehl H and Dech S. 2009. Urbanization in India-Spatiotemporal analysis using remote sensing data. *Computers, Environment and Urban Systems*, **33**(3): 179–188 DOI: 10.1016/j.compenvurbsys.2008.09.003

Wang Q, Zhang Z X, Yi L, Tan W B and Wang C Y. 2007. Research on urban expansion in Nanjing, China using RS and GIS. *Resources and Environment in the Yangtze Basin*, **16**(5): 554–559

Xu X Q, Zhou Y X and Ning Y M. 1997. Urban Geography. Beijing: Higher Education Press

Zhang W B, Fang X Q and Zhang L S. 1999. Method to identify the urban-rural fringe by TM images. *Journal of Remote Sensing*, **3**(3): 199–203

Zha Y, Ni S X and Yang S. 2003. An effective approach to automatically extract urban land-use from TM imagery. *Journal of Remote Sensing*, **7**(1): 37–41

应用图像卷积运算提取城市范围

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摘　要：通过一种卷积算法，从遥感分类数据中计算城市用地比例，并以该比例作为划分城市和非城市区的阈值，进而提取城市范围。方法构建了评价提取结果的指标体系，以确定卷积模板大小和阈值的选取。以北京为研究区，利用2007年SPOT 5多光谱影像分类数据，对方法的可行性进行了验证。结合统计数据中的建成区面积，采用504种模板和阈值组合进行提取试验，讨论了模板和阈值对提取结果的影响。最终选择(205, 51)的模板和阈值组合，对城市范围进行提取。研究结果表明：(1)该方法解决了遥感监测的城市用地分布区与城市范围存在差异的问题，为城市研究基础数据的准备提供了新的方法；(2)阈值过高或过低会造成城市范围的明显缩小或扩大；较小的模板不利于消除随机误差，较大的模板则会导致结果过于平滑；(3)对于SPOT 5多光谱影像分类数据，模板大小在193—205像元(约4 km^2)、阈值接近50时，提取结果最好。

关键词：城市范围提取，遥感检测，卷积运算，城市用地比例，北京

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1　引　言

在人口快速增长、城市化进程加速的今天，城市的形态、扩展模式、动态模型和空间结构等研究已经成为地理学研究的热点问题(牟凤云 等，2007)。城市范围的确定是进行这些城市研究的基础。在城市研究中，遥感数据是一种正在被广泛使用的重要数据源(Longley，2002)。遥感具有快速、准确和周期性动态监测等特点，可为城市研究提供多时相的监测数据，同时，图像处理方法和信息提取技术的发展和完善，为遥感影像信息提取提供了理论依据和技术支持。目前，遥感监测已经成为城市监测研究中的主要方法。

利用遥感技术进行城市监测研究，主要内容是提取城市用地。遥感提取的城市用地，是根据建筑物的光谱特征提取其土地覆盖中的建筑物分布区域，属于土地覆盖的类型，通常将其作为城市范围进行城市的研究。在方法上，针对遥感光谱特征，有通过目视解译、遥感分类方法或信息提取、遥感指数提取等。例如，通过对遥感影像进行目视解译和屏幕数字化勾画城市用地(牟凤云 等，2007；王茜 等，2007)；通过遥感影像分类得到城市用地(Jacquin 等，2008；Taubenbock 等，2009；Bhatta 等，2010)；利用光谱指数或指数模型，从遥感影像中提取城市用地(查勇 等，2003；李俊杰 等，2008；李雪瑞 等，2009)。

城市是具有一定人口规模，并以非农业人口为主的居民集居地，具有区域性和综合性的特点(许学强 等，1997)。在城市地理的研究中，城市范围确定的最主要指标是城市人口的密度，同时城市的功能、城市设施(如水电保障、广场、绿地、公园、

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博物馆等)也作为城市划界的依据，城市范围的确定是按照土地利用的特征进行的。遥感监测提取的城市用地，与地理学研究关注的城市范围是不相同的。它实际上是指一种土地覆盖类型，是包括了土地利用的居民地、工业、仓储工矿用地、交通用地和建设用地等类型的达到遥感监测尺度的建筑物分布区域用地。城市范围，是城市实体在空间上的连续分布区域，它包括了多种土地覆盖类型，除建筑用地外，还包括植被和水体等土地覆盖类型。遥感监测的较高密度的城市用地是城市的核心区，与城市范围在数量上和地域空间上均存在一定差别。

为了解决遥感监测的城市用地分布区与城市范围的差异，将遥感监测成果转化为城市研究的基础数据，本文提出了利用遥感监测的城市用地的量化指标—城市用地比例，来提取城市范围的方法。研究区为北京市，利用2007年遥感影像分类数据，对本方法进行了可行性验证。

2 提取方法

根据城市范围确定的综合性特点，城市建筑物的密度达到一定比例可作为城市边界划分的标准(章文波 等，1999)。通过卷积运算、城市判别和聚类统计等步骤，进行城市范围的提取。具体过程为，通过图像卷积运算，从遥感影像分类结果中计算城市用地比例。然后，以城市用地比例作为区分城市和非城市的阈值，对城市进行判别。最后，通过聚类分析从判别结果中提取城市范围。流程如图 1 所示。

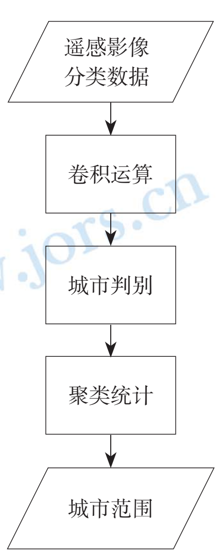

图1 城市范围提取流程

2.1 城市用地比例计算

城市用地比例是通过图像卷积运算得到的(章文波 等，1999)。卷积运算在空间域上对图像进行邻域检测，是遥感图像处理中常用的方法，可用于各种类型的图像平滑、信号处理转换、分化和边缘检测等。卷积运算通过一个选定的卷积函数来实现，卷积函数又称为“模板”， 实际上是一个$M\times N$的小图像。具体算法如下(汤国安 等，2004)：

选定大小为$M\times N$的运算模板$\varphi(m, n)$，在图像上开一个与模板同样大小的活动窗口$f(m, n)$，使图像窗口与模板像元的灰度值对应相乘再相加。计算结果$g(i, j)$作为图像中心像元的灰度值。模板运算的公式为：

$$g(i,j)=\sum_{m=1}^{M}\sum_{n=1}^{N}f(m,n)\varphi(m,n) \tag{1}$$

然后沿同一行将模板向右移动一列，图像上的窗口也对应移动，按式(1)计算，并把结果作为新窗口中心像元的灰度值，依此类推，产生新的图像。卷积运算时，由于新的灰度值处在窗口的中心，所以模板的大小一般取奇数，且$M=N$。

在本研究中，计算城市用地比例时，卷积函数的模板采用$M\times N$的均值平滑模板，即$\varphi(m, n)=1$。计算公式为：

$$\begin{cases} g(i,j)=\dfrac{1}{N^2}\sum_{m=1}^{N}\sum_{n=1}^{N}f(m,n)\times 100 \\ f(m,n)=\begin{cases}1,\ \text{城市}\\ 0,\ \text{非城市}\end{cases} \end{cases} \tag{2}$$

式中，$f(m, n)$为遥感影像分类结果。当用地类型为城市用地时，值为1；为非城市用地时，值为0。$g(i, j)$的取值为0—100，代表像元(i, j)的城市用地比例(%)。

2.2 判别和提取

对式(2)的计算结果$g(i, j)$进行城市判别：设置阈值t，通过式(3)，计算得到新图像$G(i, j)$：

$$G(i,j)=\begin{cases}0,\ g(i,j)\in[0,\ t]\\ 1,\ g(i,j)\in(t,\ 100]\end{cases} \tag{3}$$

判别结果$G(i, j)$中既包含了城市范围，也包括城市周边独立分布，或是郊区区县、乡镇面积达到一定规模的居民区。通过对判别结果进行聚类统计，提取面积最大图斑的外边界作为城市范围，从而消除这些居民

区对提取结果的影响。

2.3 模板和阈值确定

在提取城市范围的过程中，卷积运算时卷积模板的大小和用于城市判别的城市用地比例阈值(以下分别简称为模板、阈值)是城市范围确定的关键。阈值过低会夸大城市范围，而阈值过高则会缩小城市范围。模板的选择与城市用地和非城市用地的斑块大小、空间结构有关。模板太小，卷积运算难以剔除随机变化的影响；模板太大，卷积运算又会导致城区城市用地比例值过低(章文波 等，1999)。

通过分析模板和阈值对提取结果面积精度的影响，确定最佳模板和阈值组合。设置模板集合$\boldsymbol{K}$和阈值集合$\boldsymbol{T}$。集合$\boldsymbol{K}$中包含a个不同大小的模板，模板编号记为$\boldsymbol{K}_x$，x=1，2，…，a；集合$\boldsymbol{T}$中包含b个不同的阈值，阈值编号记为$\boldsymbol{T}_y$，y=1，2，…，b。将这两个集合中的元素组合，用每一个组合对城市范围进行提取，得到$a\times b$个提取结果。

采用两个指标来评价提取结果面积的相对精度：平均精度和标准差；用两个指标来衡量提取结果面积的绝对误差：均方根误差和偏差。将模板和阈值组合为($\boldsymbol{K}_x$，$\boldsymbol{T}_y$)时提取的城市范围的面积记为A_{xy}，城市范围真实面积记为A_0。各指标定义如下：

2.3.1 平均精度

P_{xy}表示模板为$\boldsymbol{K}_x$、阈值为$\boldsymbol{T}_y$时的提取精度：

$$P_{xy}=\left[1-\frac{|A_{xy}-A_0|}{A_0}\right]\times 100\% \tag{4}$$

$\overline{P_x}$表示模板为$\boldsymbol{K}_x$时，城市范围提取的平均精度：

$$\overline{P_x}=\sum_{y=1}^{b}P_{xy}/b \tag{5}$$

$\overline{P_y}$表示阈值为$\boldsymbol{T}_y$时，城市范围提取的平均精度：

$$\overline{P_y}=\sum_{x=1}^{a}P_{xy}/a \tag{6}$$

2.3.2 平均精度的标准差

平均精度的标准差反应提取的城市范围面积的平均精度的波动情况，即平均精度的离散程度。$\overline{\delta_x}$代表模板为$\boldsymbol{K}_x$时，城市范围提取平均精度的标准差。

$$\overline{\delta_x}=\frac{\sum_{y=1}^{b}\left|P_{xy}-\overline{P_x}\right|^2}{b} \tag{7}$$

$\overline{\delta_y}$代表阈值为$\boldsymbol{T}_y$时，城市范围提取平均精度的标准差。

$$\overline{\delta_y}=\frac{\sum_{x=1}^{a}\left|P_{xy}-\overline{P_y}\right|^2}{a} \tag{8}$$

2.3.3 均方根误差和偏差

均方根误差和偏差反应提取的城市范围面积的与真实城市范围面积之间偏离程度的平均水平。

$RMSE_x$和$bias_x$分别表示模板为$\boldsymbol{K}_x$时，提取的城市范围面积与真实城市范围面积之间的均方根误差和偏差。

$$RMSE_x=\sqrt{\sum_{y=1}^{b}(A_{xy}-A_0)^2/b} \tag{9}$$

$$bias_x=\sum_{y=1}^{b}(A_{xy}-A_0)/b \tag{10}$$

$RMSE_y$和$bias_y$分别表示阈值为$\boldsymbol{T}_y$时，提取的城市范围面积与真实城市范围面积之间的均方根误差和偏差。

$$RMSE_y=\sqrt{\sum_{x=1}^{a}(A_{xy}-A_0)^2/a} \tag{11}$$

$$bias_y=\sum_{x=1}^{a}(A_{xy}-A_0)/a \tag{12}$$

3 提取试验

3.1 研究区和数据

北京地处华北平原北端，位于39°26′N—41°04′N, 115°24′E—117°31′E之间。全市土地面积16410 km^2，其中平原面积6338 km^2，占38.6%。根据2000年北京城市总体发展规划，划分为首都功能核心区、中心城市功能拓展区、城市发展新区和生态涵养区。规划中北京市城市城区的范围是北京五环路以内。近年来随着城市化进程的加快，先后有数个近郊县改为区。由于北京市政治、文化中心的定位，工业中心正在逐渐外移。据统计资料显示，截至2007年底，北京市建成区面积达1289.3 km^2，常住人口1633万人，全年实现地区生产总值9006.2亿元。

采用北京市2007年SPOT 5影像分类数据，包括林地、草地、园地、耕地、菜地、建筑用地、未利用地和水体8种地类。通过混淆矩阵分析，分类的总体精度为83.22%，Kappa系数为0.8063。该数据是由5景SPOT 5多光谱影像，通过影像镶嵌、最大似然法分类得到的，覆盖了北京市平原区和部分山区。这5景SPOT 5影像简介见表 1。

表1 研究使用的SPOT 5影像

影像编号	轨道号(K–J)	成像时间
1	279–268	2007–04–24
2	282–269	2007–05–03
3	282–270	2007–05–03
4	280–269	2007–05–19
5	280–270	2007–05–19

3.2 模板和阈值集合

提取北京市2007年的城市范围时，所用的模板和阈值分别为：在0—6 km^{2}的面积范围内，每0.25 km^{2}取1个模板，共选择24个模板；以40—60之间的整数值作为阈值，共选择21个阈值。

试验所用部分模板如表2所示。其中， N是与模板面积相对应的、用像元数表示的模板大小，即卷积运算的$N\times N$模板。由于N必须是奇数，因此试验中选择了小于等于模板面积的最大奇数模板。

表2 城市范围提取所用的部分模板

编号	面积/km^2	N
1	0.25	49
2	0.50	69
3	0.75	85
4	1.00	99
5	1.25	111

3.3 提取结果

提取城市范围前，先对分类数据作如下处理：把建筑用地赋值为1；其他地类赋值为0，得到北京市2007年城市-非城市用地图。

将上述的24个模板和21个阈值组合，对模板和阈值的选取进行讨论，详见本文的第4部分。研究最终选取 (205, 51)的模板和阈值组合，对城市范围进行提取。提取结果如图2所示。

2007年，提取的北京市城市范围的面积为1288.79 km^2。其范围已经达到或超出六环路，覆盖了城区以及朝阳、海淀、丰台和石景山近郊4区的大部分区域，并沿着几条主要的道路到达了昌平、通州、大兴、房山和门头沟等远郊区县，形成了几个明显的城市扩展轴。如东部的京通快速路、102及103国道，东南部的京津塘高速公路，南部的京开路、106国道以及西南部的107国道，西部的京原路，109国道以及北部的八达岭高速公路等。城市范围与相应区域的SPOT 5影像叠加，如图3所示。

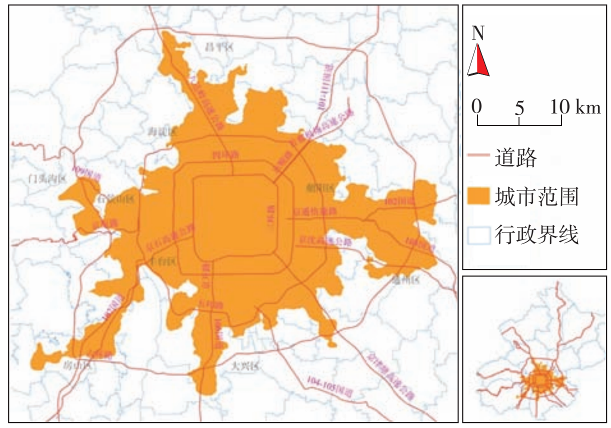

图2 北京市2007年城市范围

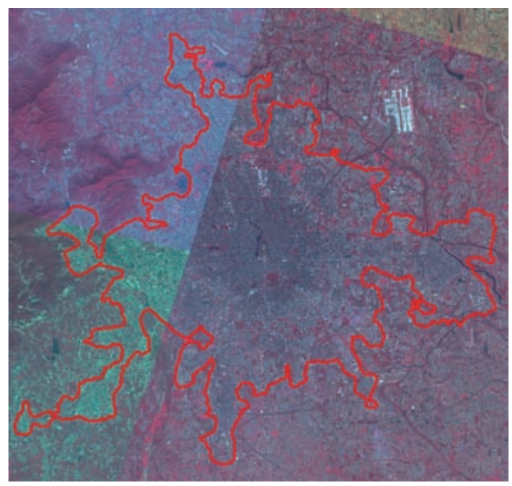

图3 城市范围与SPOT 5影像叠加

4 模板和阈值选取

城市建成区作为城市研究中最基本的城市地域概念，反映了城市作为人口和各种非农业活动高度密集的地域而区别于乡村，可以代表城市的景观地域(许学强 等，1997)。中国的统计部门用建成区来反映一个城市的城市化区域的大小。因此，本研究用城市建成区面积作为城市范围的真实面积，对模板和阈值的选取进行讨论。

4.1 阈值对提取精度的影响

在阈值$\boldsymbol{T}_y$下，提取结果的平均精度、平均精度的标准差、均方根误差和偏差如图4所示。

如图4(a)所示，随着阈值的增加，平均精度先升高，后降低。当阈值为51时，平均精度最高。如图4(b)所示，随着阈值的增加，平均精度的标准差总体上呈现出下降的趋势，并在部分阈值范围内出现波

动。当阈值为50时，标准差最小；阈值大于50后，标准差增大，但增大的趋势不明显。如图4(c)所示，随着阈值的增加，均方根误差先减小，后增加。当阈值为51时，均方根误差最小。如图4(d)所示，随着阈值的增加，偏差减小。当阈值为51时，偏差的绝对值最小。综合4个评价指标表明，阈值对提取结果影响很大，当阈值在50附近时，提取结果的面积精度最佳。

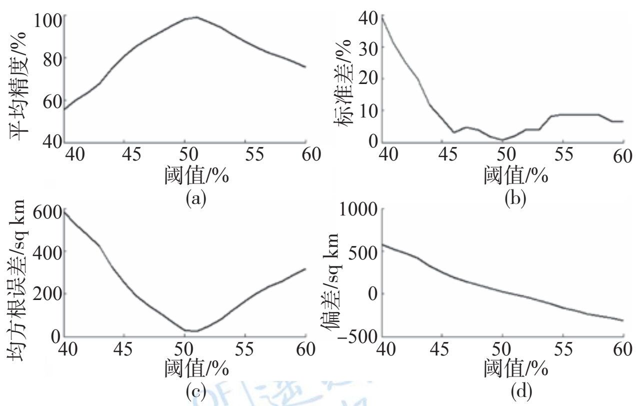

图4　阈值对提取精度的影响

(a) 平均精度；(b) 标准差；(c) 均方根误差；(d) 偏差

4.2　模板对提取精度的影响

在模板$\boldsymbol{K}_x$下，提取结果的面积平均精度、平均精度的标准差、面积的均方根误差和偏差如图5所示。

如图5(a)所示，随着模板大小增加，平均精度总体上呈现下降趋势。如图5(b)所示，随着模板大小增加，平均精度的标准差呈增大的趋势。模板大于165之后，标准差曲线趋于平缓。如图5(c)所示，随着模板大小增加，均方根误差总体上呈现增大的趋势。同样，在模板大于165之后，均方根误差曲线趋向平缓。如图5(d)所示，随着模板大小增加，偏差先增大，随后减小，当模板大于149后，偏差变化很小，偏差曲线趋于平缓。

从上述分析可知，模板大小对提取结果的面积精度有较大的影响。随着模板大小增加，平均精度下降。当模板在49—157范围内时，平均精度的标准差、面积的均方根误差和偏差均出现明显的变化，当模板大于157后，这3个指标的变化都趋于平缓。这说明在较小的模板下，提取的城市范围随机性较强，而较大的模板有利于消除随机性，但会损失一定的城市用地信息。

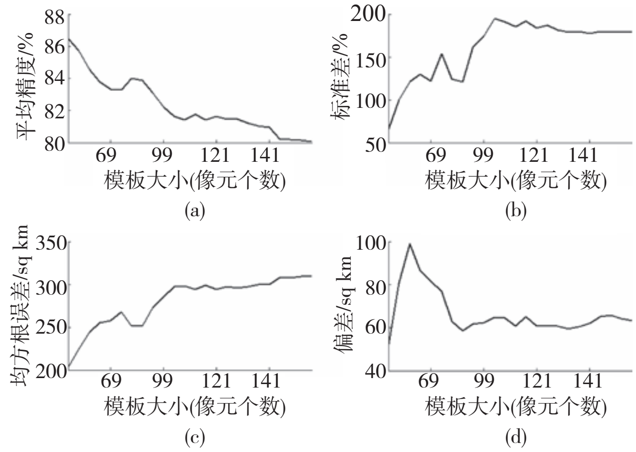

图5　模板大小对提取精度的影响

(a) 平均精度；(b) 标准差；(c) 均方根误差；(d) 偏差

4.3　最佳模板和阈值组合

通过精度分析可知，当阈值在50附近时，提取精度最佳。阈值为50、51、52时，提取结果的面积如图6所示。从图中可以看出，模板大小为193—205时，3个阈值的面积变化都趋于平缓。结合上一节的分析，认为该范围内的模板是最佳模板。当阈值为51、模板大小为205时，提取结果的精度最高，因此，研究选取的最佳模板和阈值组合为(205，51)。

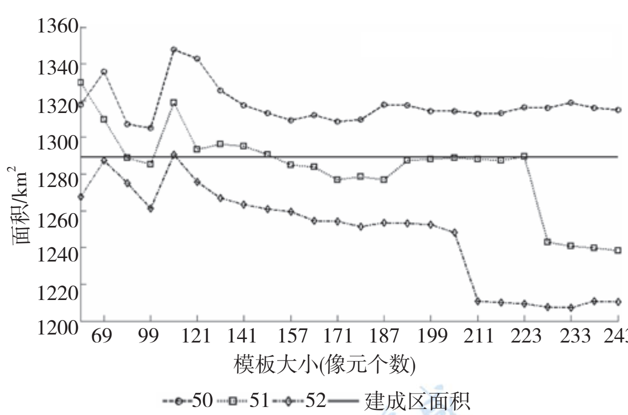

图6　模板和阈值确定

5　结论与讨论

遥感监测的城市用地与城市范围存在着较大的差异，本文提出一种从遥感监测结果中提取城市范围的方法。该方法利用遥感影像分类数据，通过卷积运算得到城市用地比例，然后提取比例高于一定阈值的区域作为城市范围。研究以北京市为例，利用2007年

SPOT 5影像分类数据，结合建成区面积统计数据，确定了城市范围。研究所得的北京市2007年的城市范围面积为1288.79 km^2，与2007年建成区面积相差0.51 km^2。从提取结果的空间分布看，2007年北京市的城市范围已经超出五环路，在部分区域已经达到或超出六环路。城市沿着主要的高速公路和国道分布，形成了明显的城市轴带。

在城市范围的提取过程中，模板大小和阈值的选择最为关键。研究通过构建面积精度评价指标，选取504个模板和阈值组合，讨论了模板和阈值的选取。结果表明，阈值对城市范围的提取有直接的影响，阈值过高或过低都会造成城市范围的明显缩小或夸大。当阈值在50左右时，提取结果的精度最佳。模板大小对精度的影响相对较小，但较小的模板不利于消除随机误差，而较大的模板会导致卷积运算结果过于平滑，影响城市范围提取的精度。当模板大小在193—205(约4 km^2)时，结果最佳。研究最终采用(205，51)的模板和阈值组合对城市范围进行提取。

本研究只进行了基于SPOT遥感影像分类数据的城市范围提取实验。对于其他数据源，方法中的模板和阈值均会存在差异，这有待进一步研究。另外，本文方法建立在遥感分类数据基础上，分类精度对提取结果会有直接影响。

REFERENCES

Bhatta B, Saraswat S and Bandyopadhyay D. 2010. Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data. *Applied Geography*, **30**(1): 96–111 DOI: 10.1016/j.apgeog.2009.08.001

Jacquin A, Misakova L and Gay M. 2008. A hybrid object-based classification approach for mapping urban sprawl in periurban environment. *Landscape and Urban Planning*, **84**(2): 152–165 DOI: 10.1016/j.landurbplan.2007.07.006

Li J J, He L H, Dai J F, Li X C and Fu Q Y. 2008. Urban sprawl study based on impervious surface percent. *Remote Sensing Technology and Application*, **23**(4): 424–427

Li X R, Wang X L and Feng Z K. 2009. Research on urban expansion based on land use degree. *Progress in Geography*, **28**(3): 398–402

Longley P A. 2002. Geographical information systems: Will developments in urban remote sensing and GIS lead to 'better' urban geography? *Progress in Human Geography*, **26**(2): 231–239 DOI: 10.1191/0309132502ph366pr

Mu F Y, Zhang Z X, Chi Y B, Liu B, Zhou Q B, Wang C Y and Tan W B. 2007. Dynamic monitoring of built-up area in Beijing during 1973–2005 based on multi-original remote sensed images. *Journal of Remote Sensing*, **11**(2): 257–268

Tang G A, Zhang Y S, Liu Y M, Xie Y L, Yang X and Liu A L. 2004. Remote Sensing Digital Image Processing. Beijing: Publisher of Science

Taubenböck H, Wegmann M, Roth A, Mehl H and Dech S. 2009. Urbanization in India-Spatiotemporal analysis using remote sensing data. *Computers, Environment and Urban Systems*, **33**(3): 179–188 DOI: 10.1016/j.compenvurbsys.2008.09.003

Wang Q, Zhang Z X, Yi L, Tan W B and Wang C Y. 2007. Research on urban expansion in Nanjing, China using RS and GIS. *Resources and Environment in the Yangtze Basin*, **16**(5): 554–559

Xu X Q, Zhou Y X and Ning Y M. 1997. Urban Geography. Beijing: Higher Education Press

Zhang W B, Fang X Q and Zhang L S. 1999. Method to identify the urban-rural fringe by TM images. *Journal of Remote Sensing*, **3**(3): 199–203

Zha Y, Ni S X and Yang S. 2003. An effective approach to automatically extract urban land-use from TM imagery. *Journal of Remote Sensing*, **7**(1): 37–41

附中文参考文献

李俊杰，何隆华，戴锦芳，李杏朝，傅俏燕. 2008. 基于不透水地表比例的城市扩展研究. 遥感技术与应用，**23**(4): 424–427

李雪瑞，王秀兰，冯仲科. 2009. 基于土地利用程度的北京城市扩展特征. 地理科学进展，**28**(3): 398–402

牟凤云，张增祥，迟耀斌，刘斌，周全斌，王长有，谭文彬. 2007. 基于多源遥感数据的北京市1973–2005年间城市建成区的动态监测与驱动力分析. 遥感学报，**11**(2): 257–268

汤国安，张友顺，刘咏梅，谢元礼，杨昕，刘爱利. 2004. 遥感数字图像处理. 北京: 科学出版社

王茜，张增祥，易玲，谭文斌，王长有. 2007. 南京城市扩展的遥感研究. 长江流域资源与环境，**16**(5): 554–559

许学强，周一星，宁越敏. 1997. 城市地理学. 北京: 高等教育出版社

章文波，方修琦，张兰生. 1999. 利用遥感影像划分城乡过渡带方法的研究. 遥感学报，**3**(3): 199–203

查勇，倪绍祥，杨山. 2003. 一种利用TM图像自动提取城镇用地信息的有效方法. 遥感学报，**7**(1): 37–41