Texture feature Extraction for Land-cover Classification of Remote Sensing Data in Land Consolidation District Using Semi-variogram analysis

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Abstract: The areas of the land consolidation projects are generally small, so the remote sensing images used in land-cover classification for the land consolidation are generally high spatial resolution images. The spectral complexity of land consolidation objects results in specific limitation using pixel-based analysis for land cover classification such as farmland, woodland, and water. Considering this problem, two approaches are compared in this study. One is the fixed window size co-occurrence texture extraction, and another is the changeable window size according to the result of semi-variogram analysis. Moreover, the methodology for optimizing the co-occurrence window size in terms of classification accuracy performance is introduced in this study. Zhaoquanying land consolidation project is selected as an example, which located in Shunyi District, Beijing, China; texture feature is extracted from SPOT5 remote sensing data in the TitanImage development environment and involved in classification. Accuracy assessment result shows that the classification accuracy has been improved effectively using the method introduced in this paper.

Key-Words: Semi-variogram, Land Consolidation, Texture feature, Classification

1 Introduction

Remote sensing image plays an important role in the information extraction for land consolidation project. Pixel-based classification methods (including supervised classification method and non-supervised classification method) are not capable of extracting information aquiring from the high spatial resolution remote sensing data (SPOT5 2.5m, IKNOS 1.0m, QuickBird 0.61m) due to spectral instability of high spatial resolution images [1]. Pixel-based approaches greatly depend on the spectral information, and neglect some important information of high spatial resolution image, such as texture features, shape features, neighborhood information, and context information etc.

Texture feature is an important characteristic for the analysis of many types of images, especially in high spatial resolution images [2]. Therefore, traditional land cover classification methods can't be applied to the classification of high spatial resolution images. A new classification approach is needed that takes into account not only the spectral characteristics of single pixels but also those of surrounding (texture feature) pixels.

Extraction of texture features from high spatial resolution remote sensing imagery provides a complementary source of data for those applications in which the spectral information is not sufficient for land-cover classification of spectrally heterogeneous land consolidation district. Pixel-based classification methods utilizing the texture feature have already become a hot research issue in the domain of image information extraction. There is a wide range of textural analysis techniques that are used with different criteria for feature extraction: statistical methods (grey level co-occurrence matrix, semi-variogram analysis), filter techniques (energy filters, Gabor filters), or the most recent techniques based on wavelet decomposition [3] [4]. Texture analysis has become an important means increasing the accuracy of remote sensing image classification.

Co-occurrence matrix is the most common and wide method used in the statistical texture analysis, through which the spatial relationship of the pixels is researched to describe the remote sensing image. However, the texture features are closely related to image scale [5], the gray co-occurrence matrix uses the scale information to discriminate between patterns and doesn't assume that a pattern could occur at different scales. So it is very important to determinate the scale of texture analysis applies in remote sensing image classification, corresponding to choosing an appropriate texture window size for gray co-occurrence matrix texture analysis. In order to select an appropriate texture window size and improve land cover classification accuracy, a new method of classification combining texture feature based on semi-variogram is proposed in this paper. Curran [6] showed the possibility of using the variogram in remote sensing. The variogram relates variance to distance and provides a concise and unbiased description of the scale and pattern of spatial variability [7].

Land consolidation has become one of the significant tools for urban land management in developed countries [8], but it mainly applied for agricultural land settlement in developing countries. The purpose of the land-cover classification for land consolidation projects is to determine which variables can count changes in agricultural land, and apply evaluation criteria for the land consolidation effect by the calculation of several indices and the use of GIS technology. This paper studies the spatial relationship between the adjacent pixels in the remote sensing image, and selects the lag distance of the semi-variogram that is determined when the value of the semi-variogram tends to be constant as the co-occurrence window size, and under the restraint of supervised Maximum Likelihood Classification results to compute the co-occurrence features with a timely changeable co-occurrence window size according to the semi-variogram analysis. The experimental results demonstrate that this method can be successfully applied in classification land cover of land consolidation projects.

The paper is organized as followed. In section 2, the theory foundation is provided with the description of the co-occurrence and semi-variogram function, and their roles in extracting the texture feature is briefly discussed. In Section 3, the details of the study area and the preprocessing procedures of remote sensing image are introduced. The texture feature extraction and semi-variogram analysis are discussed in Section 4. Experimental results are presented and discussed in Section 5. At last section 6 concludes this work and outlines some directions of future research.

2 Related Works and the Proposed Method

2.1 Co-occurrence Matrix

The Gray Level Co-occurrence Matrix (GLCM) has been defined by Haralick [9]. A co-occurrence matrix is a square matrix whose elements correspond to the relative frequency of occurrence of gray level values of pixels pairs separated by a certain distance in a given direction [10]. As shown in Fig.1, where $(\Delta x, \Delta y)$ represents distance between two pixels, i and j are the DN value of pixels, d is the distance between two pixels. The gray level co-occurrence matrix is defined as:

$$P(i, j, d, \theta)(i, j = 0, 1, 2, \cdots, N-1) \qquad (1)$$

Where the number of gray series is N , θ is the angle between the X-axis and a vector extending from a pixel to another pixel.

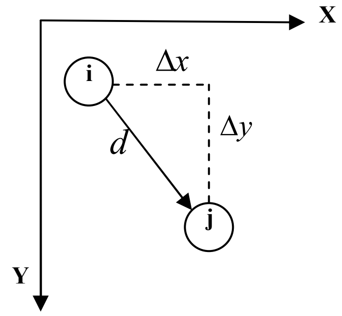


Fig.1 Gray Level Co-occurrence Matrix

The GLCM contains comprehensive information of image pattern, such as direction, partial neighborhood, changing range, however, they can't be used to extract regional texture directly, and the main limitation of traditional GLCM multi-scale texture classification algorithms is that two similar patterns reproduced at different scales on the image will be considered different patterns [11]. Therefore, in order to describe texture feature exactly, extracting texture feature from the gray level co-occurrence matrix using flexible window size is necessary.

Many texture features, such as homogeneity, contrast, mean, angular second moment, have been proposed to measure spatial patterns of remote sensing images for statistical textural analysis using the gray level co-occurrence matrix [12]. It is common practice to utilize 14 well-known Haralick's coefficients [9] as the co-occurrence matrix-based features. All features are described in Table1.

2.2 Semi-variogram

The semi-variogram function describing the spatial variation of samples as a function their apart distance is an intermediary in geo-statistical calculation [13], while the semi-variogram function is the primary tool [14-17] of geo-statistical applications such as Kriging or conditional simulation [18].

The semi-variogram was firstly put forward by Matheron G. in 1960s [19]. The theoretical foundation and study object of semi-variogram are region variation distributed rule in spatial range and time-spatial range [20]. To describe the semi-variogram spatial variant structure of the remote sensing data, the mathematic structure model of the semi-variogram is defined as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \qquad (2)$$

Where $\gamma(h)$ represents the values of semi-variogram, while h is the separation distance between two samples, $N(h)$ is equal to the number of value pairs in which the separation distance is equal to h, $Z(x_i)$ is calculated using x_i, which is corresponding to DN value of the remote sensing image.

Table 1 Features in Haralick's co-occurrence-based method for texture analysis

Feature	*Definition*
Angular second moment	$f_1 = \sum_i \sum_j p(i,j)^2$
Contrast	$f_2 = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N} \sum_{\substack{j=1 \\ \lvert i-j \rvert = n}}^{N} p(i,j) \right\}$
Correlation	$f_3 = \dfrac{\sum_i \sum_j (i,j) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$
Sum of squares: variance	$f_4 = \sum_i \sum_j (i-\mu)^2 p(i,j)$
Inverse difference moment	$f_5 = \sum_i \sum_j \dfrac{1}{1+(i-j)^2} p(i,j)$
Sum average	$f_6 = \sum_{k=2}^{2N} k p_{x+y}(k)$
Sum variance	$f_7 = \sum_{k=2}^{2N} \left\{ (k-f_6)^2 p_{x+y}(k) \right\}$
Sum entropy	$f_8 = -\sum_{k=2}^{2N} p_{x+y}(k) \log\left\{ p_{x+y}(k) \right\}$
Entropy	$f_9 = -\sum_i \sum_j p(i,j) \log\left\{ p(i,j) \right\}$
Difference variance	$f_{10} = \sum_{k=0}^{N-1} \left[k - \sum_{l=0}^{N-1} l p_{x-y}(l) \right]^2 p_{x-y}(k)$
Difference entropy	$f_{11} = -\sum_{k=0}^{N-1} p_{x-y}(k) \log\left\{ p_{x-y}(k) \right\}$
Measures of correlation 1	$f_{12} = \dfrac{f_9 - HXY_1}{\max(HX, HY)}$
Measures of correlation 2	$f_{13} = \sqrt{1 - \exp\left[-2(HXY_2 - f_9) \right]}$
Max. correlation coefficient	$f_{14} = \sqrt{\text{Second largest eigenvalue of Q}}$

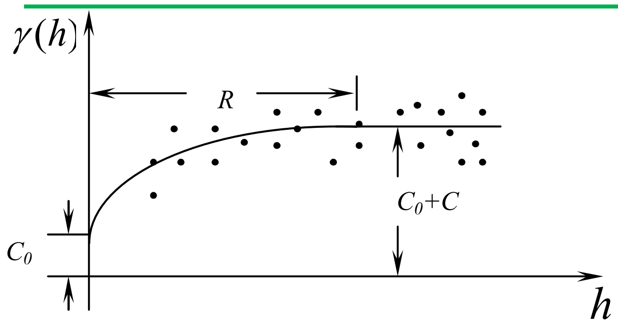


Fig.2 The semi-variogram function curve

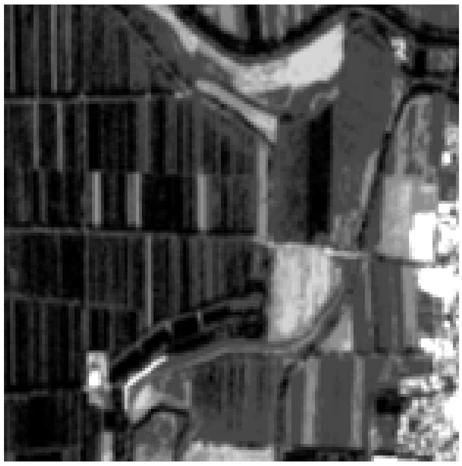
Semi-variogram function is typically expressed in semi-variogram curve. The semi-variogram curve is shown in Fig.2.

The semi-variogram curve indicates the relationship between semi-variogram function values $\gamma(h)$ and sample distance h. Nugget, Sill and Range are three important parameters in semi-variogram's theoretical model. When $h=0$, the semi-variogram value C_0 is called Nugget, which represents special heterogeneity due to random factor. When the h is gradually increased to R, the value of the semi-variogram tended to be a relative stability constant: $C_0 + C$, which is called Sill. C represents special heterogeneity due to spatial autocorrelation, and $C_0 + C$ indicates the overall special heterogeneity and is defined as maximal semi-variogram value acquired from the data. R is called Range, the Range is an important parameter, which indicates the maximum distance of spatial dependency and is closely related to the sizes of the ground objects in remote sensing images. Woodcock *et al.* also concluded that the Sill is influenced by density of the objects, whereas the Range depends on their diameters. Moreover, variations in size distribution resulted in different shapes of the variogram close to the Range [21].

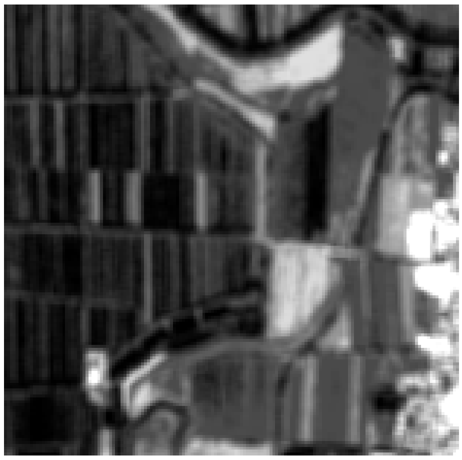
2.3 Semi-variogram-based Texture Feature Windows Determined

Main parameters used in extracting the textural information by co-occurrence matrix, includes texture feature, gray series, direction and separation distance between two pixels, window size. Dell' Acqua, F. *et al*. extracted texture feature by using co-occurrence matrix and semi-variogram analysis for mapping urban density classes in satellite SAR data. The results show that the joint use of co-occurrence texture features and semi-variogram analysis to optimize co-occurrence window size can be, in terms of classification accuracy performance, as effective as a long exhaustive search of the best scale [22]. The textural bands of Heterogeneity using different window size (3*3, 7*7, 11*11) are shown in Fig. 3.

(a) 3*3



(b) 7*7



(c) 11*11

Fig.3 Heterogeneity features extracted using fixed texture window

As shown in the Fig. 3, the texture window size affects the texture features extraction to a certain extent [23]. When texture window is relatively small, the textural information extracted is fragmentized, and more details are manifest and more spots exist in textural information; on the other hand, the information of small targets may be filtered and the boundaries of objects are fuzzed, so that neither can acquire the satisfied results. When the texture features are extracted using fixed window in classification, the overall classification accuracy can improve to a certain extent, however, with the window gradually increasing, the overall classification accuracy begin to reduce. Window size for classification accuracy of the different categories is different. When window size smaller than 9*9 pixels is used, the classification accuracy of the farmland is gradually increasing, reversely, the classification accuracy of woodland is gradually decreasing.

This paper describes the spatial relationship between the adjacent pixels in remote sensing image according to semi-variogram value of samples, and selects the lag distance of the semi-variogram. The value of selected semi-variogram tended to be constant to the co-occurrence window size, which is the most important influencing factor in the texture features extraction process [24].

3 Study Area and Data Preparation

The study area shown in Fig.4 is selected in the northwestern land consolidation area in Zhaoquanying, Shunyi District, which is located in north-east of Beijing, covering an area of 1021 km^2. The geographic coordinates (latitude/longitude) approximately range from 116°58' E, 40°00'N to 116°58'E, 40°18'N. This area is characterized by rice-farmland and flourishing vegetation. This region is one of the fastest growing centers of land consolidation in Beijing. The typical land-cover classes include: residential area, farmland, woodland, grassland and barren/soil.

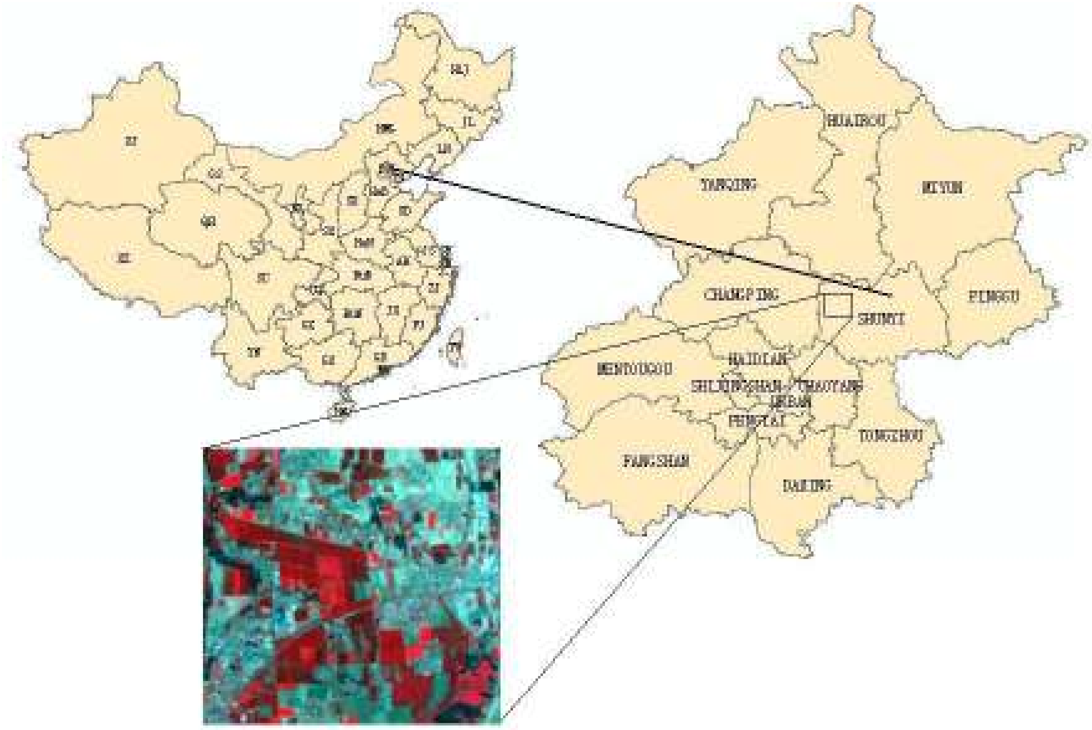


Fig.4 Study site in Zhaoquanying, Shunyi of Beijing from a SPOT5 imagery in 2006

A subset of SPOT5 remote sensing image is used in this study. The SPOT5 image consists of a panchromatic band with 2.5m spatial resolution and four multi-spectral bands (i.e. near-infrared (NIR), red, green, and Short Waved-length Infrared) with 10m spatial resolution, which were acquired in 2006 without any clouds/hazes. All bands of imagery are geo-referenced to a Transverse Mercator projection and Krasovsky spheroid with an RMSE less than 1 pixel. The SPOT5 remote sensing image has to be preprocessed, including geometric calibration to the multi-spectral band data with the panchromatic band data and HSV fusion for the results after correction with panchromatic data, and the resolution of the final result is the same as that of the panchromatic band data.

4 Texture feature Extraction Process

The work flow of texture feature extraction is given in Fig.5. A same region with the rich textural information is selected in this study as a research object from the fused data and the panchromatic band data, and cuts out the 10-30 training sets as a Region Of Interest (ROI) for the different types of the land-cover, which is converted it to ASCII format in ENVI4.3 then, and joins the line-column ranks corresponding to DN value and saved as *.txt format. The *.txt data will provide information for semi-variogram analysis finally. Meanwhile, the fused image is classified with the supervised classification method of Maximum Likelihood Classification and the result is corresponded with the result of the window size analysis as constraint of the panchromatic band data to compute the co-occurrence features.

4.1 Semi-variogram Analysis

All class samplings will be carried out semi-variogram analysis respectively in GS +

software in order to obtain the window size of co-occurrence matrix suit to the specific class and determine the size of texture window. However, uncertainty exists in selection for all the classes in land-cover classifications, so the size of the ground objects must be considered comprehensively when the size of samplings is determined [25] [26]. When sampling range is relatively long, the interference of non-sample objects will be strengthened; in contrast, sample objects will be destroyed, both can't acquire precise semi-variogram features of the land-use classes. In this research, farmland's semi-variogram function curve is given in Fig.6, and texture analysis window size to each class determined finally is shown in Table 2.

4.2 Texture feature Extraction

Based on the size of texture window for each class in the land consolidation, the fused image is classified with the supervised classification method of Maximum Likelihood Classification. The result is corresponded to the result of the window size analysis of the above, which is set as constraint of the panchromatic band data to compute the co-occurrence features.

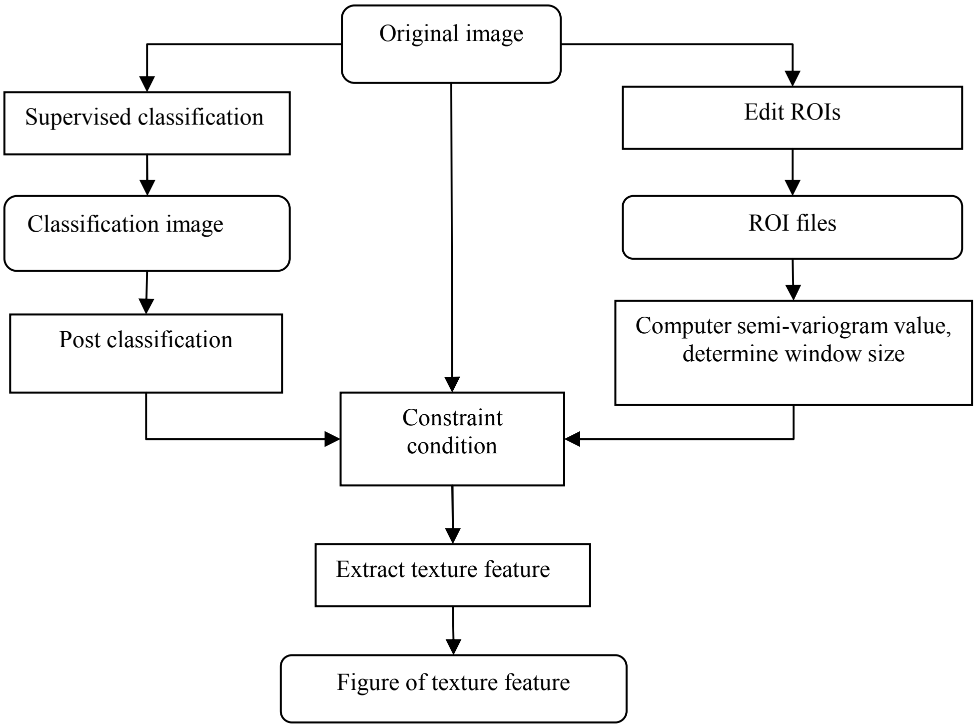


Fig.5 Texture feature extraction

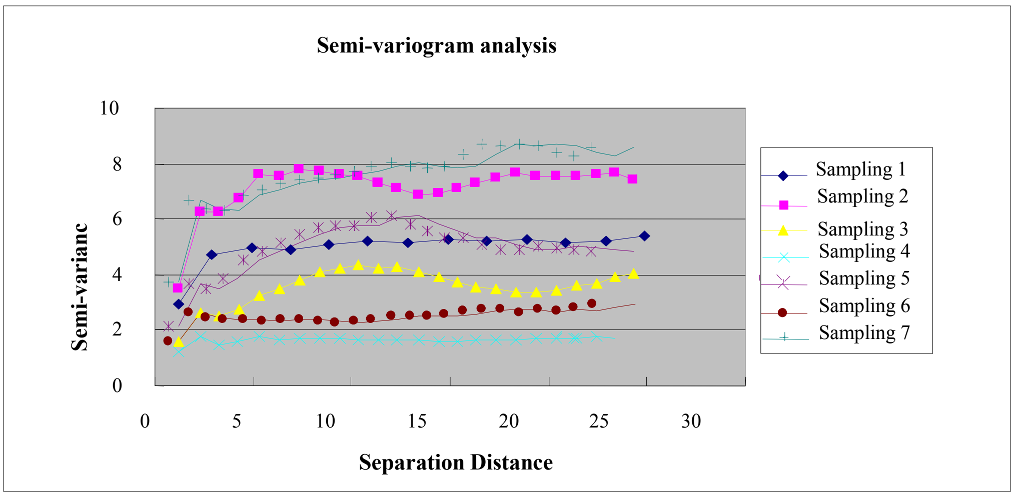


Fig.6 The experimental semi-variogram function curve of farmland

Table 2 HOM for different texture window

classes	*TextureWindowSize*
farmland 1	9*9
farmland 2	9*9
woodland	5*5
water	3*3
construction	11*11

The initial classification type of image is recorded timely during the texture feature extraction process, in order to change the window size of every pixel in the extraction process. Result of flexible window for texture feature extraction is given in Fig. 7. As shown in Fig.7, the extracted texture feature with flexible window size reduces the *Pepper and Salt effect*, and guarantees the details of image and clarity of edge compared with results extracted using fixed window which is given in Fig.3.

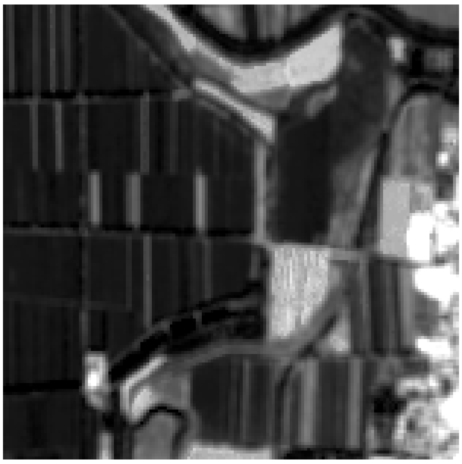
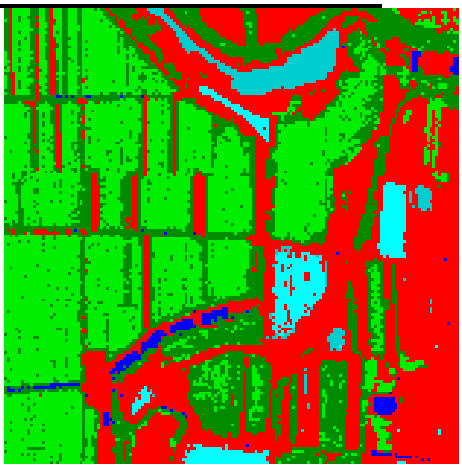


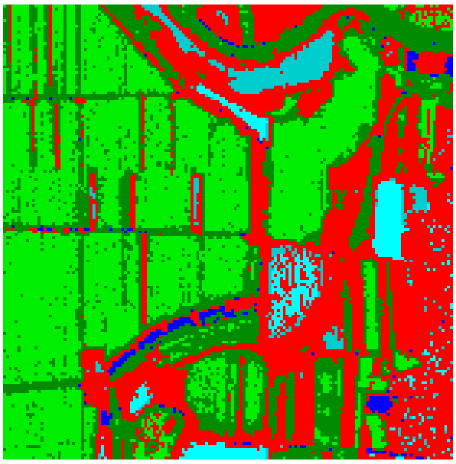
Fig.7 Mean texture feature extracted using flexible texture window size

5 Results and Discussion

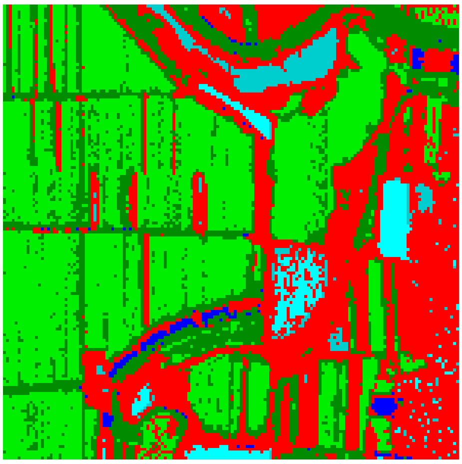
Extracted texture feature bands of remote sensing image will be combined with the bands fused images as a band, which will be carried out the supervised Maximum Likelihood Classification in the same training area. Meanwhile, the original image and the fixed window image will be classified with the Maximum Likelihood supervised classification method. All classification results are shown in Fig.8.



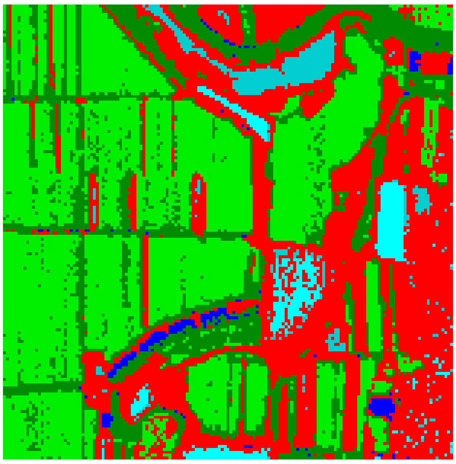
(a) Original image



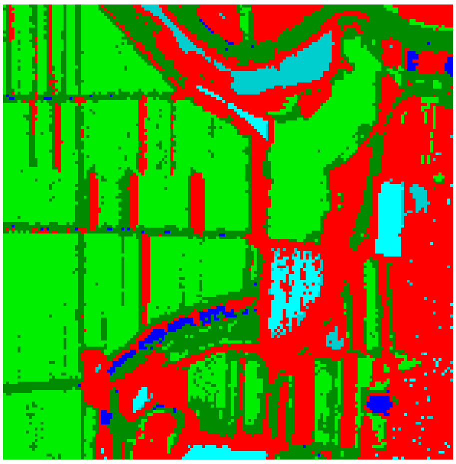
(b) 3*3



(c) 7*7



(d) 11*11



(e) Flexible window size

Fig.8 Classification results using original image and spectral + textural (mean) feature using flexible window size

As is shown in Fig.8, there are a lot of farmlands classified into woodlands. This error is due to the similarity of farmland and woodland in the spectral feature [27], but the texture feature between farmland and woodland is different, this problem is obviously improved by using the texture feature, which is extracted from the 3*3 fixed texture window. However, the *Pepper and Salt effect* is serious problem due to small texture window, especially in some construction sites. With the increase of texture window size, the *Pepper and Salt effect* has been reduced, but some details are filtered out at the same time [28]. In this paper, the method of extracting texture feature using flexible window size is adopted. It not only reduces commission and omission of farmland and other land cover classes, but also can meet the need of visual investigation.

Table 3 Accuracy assessment result

Feature / *Evaluation* / *Methods*	*Angle second-order moment*		*Homogeneity*		*Mean*		*Relativity*	
	Overall accuracy（%）	**Kappa**	**Overall accuracy（%）**	**Kappa**	**Overall accuracy（%）**	**Kappa**	**Overall accuracy（%）**	**Kappa**
Fixed window size	83.2483	0.7093	82.7347	0.7020	81.0753	0.6785	83.2483	0.7093
Flexible window size	84.7954	0.7331	86.0175	0.7476	86.4355	0.7595	84.3472	0.7255

The overall accuracy and the Kappa coefficient are estimated for every classified image. The overall accuracy for classification of the fused original image is 80.96%, Kappa is 0.68, and other evaluation results of classification image are shown in Table 3.

The maximal accuracy, which is chosen from the classification accuracy of the 3*3 pixels window to the 11*11 pixel window involved in the classification, is set as results given in the Table.3. Take the mean features as an example, the 3*3 pixel window accuracy of the classification is 81.0753%, 7*7 is 78.0169%, and 11*11 is 77.5680%. So the classification accuracy of the 3*3 pixel window is chosen as the final value of the mean feature of the fixed window. The experimental results demonstrate that the method of adding general texture feature to the classification can improve the classification accuracy to a certain extent. And the new extraction method of texture feature in this paper can improve the accuracy of the classification further. For instance, in regard to the texture measure of mean, the overall accuracy of the original fused image classification result is only 80.96%, while the overall accuracy of the classification image by adding the flexible window size texture feature rises to 86.02%, and the overall accuracy of the classification image by adding the fixed window size texture feature only gets up to 82.80%; the Kappa coefficient of the original fused image classification result is 0.68, the Kappa coefficient of the classification image by adding the texture feature with flexible window size rises to 0.75, while the Kappa coefficient of the classification image by adding the texture feature with fixed window size gets up to 0.70. Therefore, it is obvious that the accuracy of the new method developed in this study is successful for improving the classification accuracy.

When the accuracy for each object type are analyzed, it is found that the water and built areas based on original fused image can acquire better accuracy (up to 90%), but the accuracies of the farmland and woodland are relatively low (farmland: 75.38%, woodland: 84.58%). There is little change for the accuracy of farmland joining the texture feature extracted by using fixed texture window (75.81%). On the contrary, the accuracy of woodland is lower than classification based on the original image (80.52%). However, the accuracies of farmland and woodland joining the texture feature, which is extracted by using flexible texture window size, are more accurate than classification based on original image (farmland: 82.14%, woodland: 89.03%). Comparison of the results shows the accuracy is improved significantly, especially when using non-fixed window based on semi-variogram to extract texture feature.

6 Conclusion and Future Works

This paper proposes a method adding extracted texture feature by flexible window size for remote sensing image classification, the results demonstrate that the method can make full use of textural information in high-resolution remote sensing image for the land consolidation projects, especially for the farmland with rich textural information which can play an important role in discriminating it from other green plants. Comparison of the results using the flexible window size shows that the appropriate window size should be neither small nor large. Because small window size is possible to make the texture feature fragmentized, while large window size may filtered information of small targets, and the low efficiency problem will be produced by using large window size. The proposed method in this paper can be effective and sufficient for high-resolution classification. Even though the idea of the method is simple, the stable texture window size is difficult to determine for each class due to complexity and diversity of the same land feature. It requires a large number of samplings and semi-variogram analysis to improve the classification accuracy. Therefore, the actual operation may be relatively complex. In conclusion, the method proposed is still in the research stage and needs further improvement. Further work will consist of the combination of the proposed method with the pixel-based classifier and object-oriented classifier, which integrates different textural methods that will be more effective for the land consolidation projects.

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