EXTRACTING RURAL SETTLEMENT INFORMATION FROM QUICKBIRD IMAGES

Cunjian Yang[a,b], Zhen Luo [b]

[a] Research Center of Remote Sensing and GIS Applications, Key Lab of Land Resources Evaluation and Monitoring in Southwest, Ministry of Education, Sichuan Normal University, Chengdu, 610068

[b] 2 Institute of Geo-surface information technology, University of Electronic and Technology of China, Chengdu, 610068

KEY WORDS: Quickbird, image object, rural resident, segmentation, knowledge discovering

ABSTRACT:

Acquiring the information for rural settlement timely and accurately has an important significance for construction and development of rural areas. The development of remote sensing technology provides advanced means of the acquirement of the information of settlement. The study of extracting rural settlement information from Quickbird images in Xindu district, Chengdu City, P.R.of China was discussed here. Firstly, The Quickbird images such as panchromatic image and multi-spectral images were processed by geometric correction, enhancement and fusion. Secondly, the homogeneous image objects were formed by using multi-scale segmentation technology based on knowledge. Thirdly, the features such spectral feature, spatial relationship feature, texture feature and geometric feature of the image objects were obtained for each image object by using feature calculation. Fourthly, the feature knowledge of rural settlement unit and its component were obtained by using knowledge discovering. Finally, the rural settlement unit and its component information were extracted by matching the features with the feature knowledge of rural settlement unit and its component based on reasoning. It was shown that the rural settlement unit and its component information can be effectively extracted from Quickbird images by using our proposed method in this paper.

1. INTRODUCTION

The study of the distribution and inner structure characteristics of the rural settlement has the extremely vital practical significance to the construction, planning and management of the rural settlement. The rural settlement is the main pace for rural people to live in. Their appearance and inner structure can be used to present the living standard of the rural people in material and culture. Satellite remote sensing provides technology for studying the distribution of settlements. The methodologies of extracting settlements from satellite remote sensing include visual interpretation, classification, extraction based on knowledge discovering. The visual interpretation was used to extract the settlements in urban and town level in the triangle area of Yangtse river (J.F.He and D.F.Zhuang, 2006), the industrial land of Tangshan city (H.Y.Pan et al., 2007), and the settlements in urban and town level in Changsu city in China from Landsat TM/ETM images (R.H.Ma et al.,2004). The accurate result can be obtained by using the visual interpretation, which will consume a lot of labors and time. The classification method was used to extract the settlements above town level in Shanghai (X.W.Li et al.,2003), and in the triangle area of Zhujiang river from Landsat TM/ETM (W.P.Hu et al.,2003). The conventional classification method is not good for extracting settlements from the satellite remote sensing images with high spatial resolution. The method of extraction based on knowledge discovering was used to extract settlements in Fuqing city (C.J.Yang and C.H.Zhou, 2000), and Wuxi city in China (Y.Zha et al.,2003).

Settlements extracted from Landsat TM/ETM mainly are limited to the settlements in urban and town level, because of the limitation of its spatial resolution. The satellite images with high spatial resolution such as SPOT, IKONOS and QUICKBIRD images were used to obtain urban objects (G.J.Wen et al.,2003), urban building density and floor area (J.Y.Li et al.,2007). The inner structure characteristics of the rural settlement are rarely discussed. It is expensive to study the inner structure characteristics of the rural settlement by using conventional investigation technology in field. Acquiring the information for rural settlement timely and accurately has an important significance for construction and development of rural areas. The development of remote sensing technology provides advanced means of the acquirement of the information of settlement area. The study of extracting rural settlement information from Quickbird images in Xindu district, Chengdu City, P.R.of China was discussed here.

2. STDY AREA AND DATA

2.1 Study Area

The study area is Juntun town of Xindu district of Chengdu City in Sichuan Province of China. It is located in north part of Chengdu city, and in Chengdu plain, which is shown in Figure1. Its climate is of the characteristics of sub-tropical moisture monsoon, without heavy cold weather in winter and very hot weather in summer, and with the long free frown dates and the obvious four seasons. It covers 17480944 square meters, having 11 administrative villages and 1 settlement committee. There are totally twenty thousands people living in the area. Out of them, there are eighteen thousands farm persons.

2.2 Data

QUICKBIRD satellite images acquired in June 2003 were used here. The images include panchromatic band and multi-spectral bands. The characteristics of the images are shown in Table.1. Topographic map at 1:10000 scales is also used here to geometrically correct the images.

Table1. Parameters of Quickbird satellite images

Band	*Wavelength*	*Resolution(m)*
Panchromatic	450-900	0.61
Blue band	450-520	2.44

Green band	520-660	2.44
Red band	630-690	2.44
Near infrared band	760-900	2.44

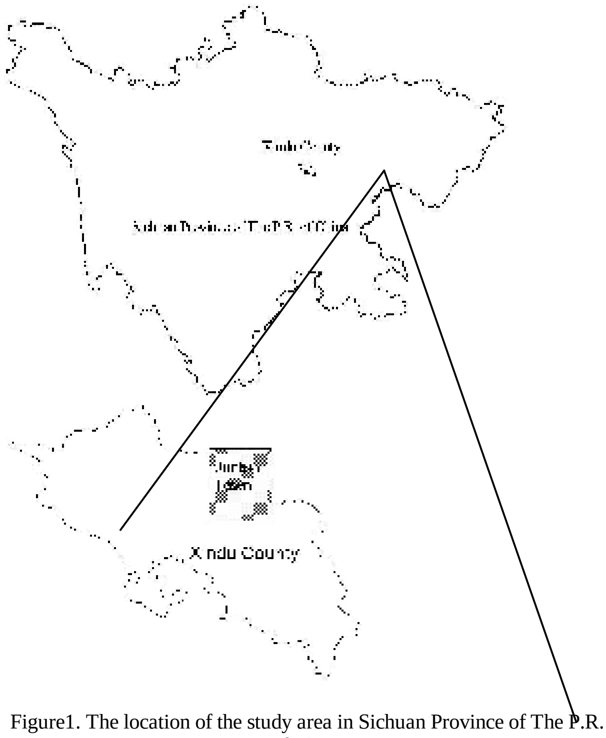

Figure1. The location of the study area in Sichuan Province of The P.R. of China

3. METHODOLGY

3.1 Image Geometrical Correction and Enhancement

Topographic map at 1:10000 scales was scanned, and geo-coded, and saved as the file in geo-tiff format. A lot pairs of control points were selected from the topographic image in geo-tiff format and the panchromatic image of Quickbird satellite. The second order polynomial transformation model was used to geometrically correct the panchromatic image of Quickbird satellite. The nearest neighbor resample algorithm was used to obtain the value of the geometrically corrected panchromatic image of Quickbird satellite. The root mean square error of thecorrection were less than or equal to one pixel.

A lot pairs of control points were selected from the geometrically corrected panchromatic image and multi-spectral band images of Quickbird satellite. The multi-spectral images of Quickbird satellite were geometrically corrected by using the second order polynomial transformation model and control points. The nearest neighbor resample algorithm was used to obtain the values of the geometrically corrected multi-spectral images of Quickbird satellite in order to avoid modification of radiometric values.

The images including panchromatic band, near infrared band, red band, green band and blue band are respectively scaled to 0 and 255. The equation as follows is used to scale the images.

$$Y(i,j) = 255 \times \frac{X(i,j) - T_1}{T_2 - T_1} \quad . (1)$$

where X(i,j)= the value of the pixel of the unscaled image
Y(i,j)= the value of the pixel of the scaled image
i , j = the location of the pixel (i,j) in the image
T2, T1 = respectively the maximum and minimum values of the pixels of the unscaled image.

The histograms of the images are used to obtain T1 and T2 for each band. For example, the histogram of the blue band is used for determining the values of T1 and T2 for the blue band, which is shown in Figure 2.

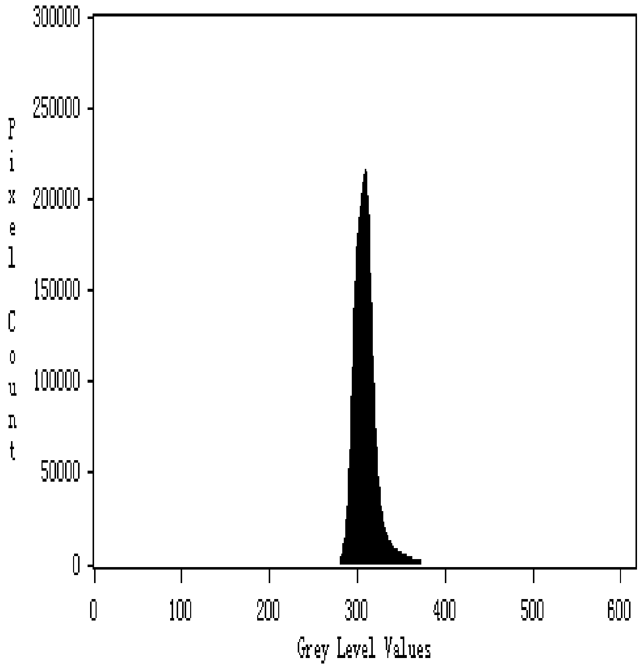

Figure2. The histogram of blue band for determining the values of T1 and T2

The histograms of the images are used to obtain T1 and T2 for each band. For example, the histogram of the blue band is used for determining the values of T1 and T2 for the blue band, which is shown in Figure.2.

3.2 Image Fusion

The fusion image was obtained by using the principal component transformation and inverse principal component transformation. Firstly, the images such as red band, green band, blue band and near infrared band were transformed into several principal components by using the principal component transformation. Secondly, the first principal component was replaced by the panchromatic band. Thirdly, the principal components with the panchromatic band instead of the first principal component were transformed into several fusion images such as red, green, blue and near infrared images by using the inverse principal component transformation. The red(R), blue(B) and green(G) images of the fusion images were selected for further study. The false color composite images were formed by presenting red,blue and green image of the fusion images with red, green and blue. The rural settlement and its components can be visually interpreted in the false colour composite image.

3.3 Multi-scale Segmentation

Image objects were obtained and inherited from the fusion images such as R, G and B by multi-scale segmentation. Firstly, the same weight was allocated among the fusion images such as R,G,B. Secondly, the images were segmented to form the first layer by using the parameter such as segmentation scale of 70, shape factor of 0.2, smoothness factor of 0.6, which was beneficial to obtain water objects from images. Thirdly, the images were segmented into the second layer by using the parameter such as segmentation scale of 40, shape factor of 0.2, smoothness factor of 0.6, which was beneficial to obtain farm patch objects from images. Fourthly, the images were segmented into the third layer by using the parameter such as segmentation scale of 20, shape factor of 0.2, smoothness factor of 0.6, which was beneficial to obtain bare land objects from images. Fifthly, the images were segmented into the fourth layer by using the parameter such as segmentation scale of 10, shape factor of 0.2, smoothness factor of 0.6, which was benefit to obtain building land objects from images. Finally, the images were segmented into the fifth layer by using the parameter such as segmentation scale of 6, shape factor of 0.2, smoothness factor of 0.6, which was beneficial to obtain building shade objects from images.

3.4 Feature Calculation

Normal difference vegetation index (NDVI) is calculated by the difference of near infrared and red divided by the sum of near infrared and red of the Quickbird satellite images.

The Grey Level Co-occurrence Matrix (GLCM) were used to process the image of Quickbird Satellite. The image of the Angular Second Moment Texture Measures (ASMTM) was computed from the GLCM.

The features such as the mean value of R, the mean value of G, the mean of B, the mean value of NIR, the mean value of NDVI and the mean value of ASMTM for each image object were obtained by respectively overlaying the images such as R, G, B, NIR, NDVI and SMTM images with image objects and calculating the mean values.

The other features such as the ratio of length to width(RLW), the shade index(SI), the area, the distance from water(DW), the distance from building (DB)were calculated for each image object.

The spatial relationship features such as the image object with boundary of building shade and the image object without boundary of building shade were also calculated for each image object.

3.5 Feature Knowledge Discovering

Feature knowledge for each class was discovered by sampling and image analysis. The feature knowledge was shown in table2.

Table2. feature knowledge for each class

class	*Feature knowledge*
Water body	NIR < 165; Area>500
Road	R>280，RLWe>3.8;SI >2.5
Bare land outside of settlement	R>275，RLW< 2.5，area>150
woodland	NDVI>0.38;ASMTM <0.07
Density vegetation land	NDVI>0.28;R< 210
Sparsely vegetation land	0.28>NDVI>0.15
Building shade	ASMTM <0.09;B<240;G<330;NIR< 210
Vegetation shade	NDVI>0.08;B<210;G<275
Building with cement roof	320>B>260;0.1> ASMTM >0.05;DW >35m
Bare landing inner residnet	300>B>260;0.1> ASMTM >0.05; DW >35m;DB <10m; Area<150m2
Building with lividity tile roof	260>B>210;0.1> ASMTM >0.05;with boundary of building shade;DW>35m
irrigated farm land	250>B>180; ASMTM >0.12;without boundary of building shade;Area>210
Other building	285>B>240;410>G>330;292>NIR>220 ;270>R>210，0.1> ASMTM >0.05;with boundary of building shade;DW >35m

3.6 Extracting Class Information

The class of each image object was identified by matching its features with the feature knowledge of each class. We used the following steps to extract class information. Firstly we obtained water body(WB) by using the feature knowledge of water body from the first layer. Secondly, road(RD) and bare land outside of settlement(BL) were extracted from the second layer by using their feature knowledge. Thirdly, the irrigated farm land (IFL)and land with vegetation(LV) was extracted from the third layer by using its feature knowledge. The building shade(BS) and the vegetation shade(VS) were extracted from the fourth layer by using their feature knowledge from the fifth layer. The building with cement roof(BCR), building with lividity tile roof(BLTR) and other building(OB) were extracted from the fourth layer by using their feature knowledge. Finally, the class layer was formed by combining all classes from each layer.

3.7 Extracting Settlement Area Information

Settlement area was composite of building, building shade, vegetation land and its shade within the settlement area, bare land within the settlement area. The feature knowledge for identifying the vegetation land within the settlement(VLS) that ASMTM is smaller than 0.08 and its distance from building is smaller than 10 meters was discovered by image analysis, which was used to extract the vegetation land within the settlement area. The settlement unit was formed by combining its building, building shade, vegetation land and vegetation shade, and bare land.

4. RESULTS AND DISCUSSION

Samples for accuracy evaluation of classes were obtained by image sampling and visual interpretation. The accuracy for classes was shown in table3. The Kappa coefficient was calculated for each class, which was shown in table4.

Table3. Accuracy of classes

calss	*test samples*	*labeled*	*true*	*Producer accuracy*	*User accuracy*
WB	35	35	35	100	100
RD	27	26	23	85	88
IFL	43	42	37	86	88
BL	46	50	36	78	72
BS	20	21	17	85	81
VS	26	22	21	81	95
BLTR	49	48	41	84	85
BCR	36	35	29	81	83
OB	45	41	34	76	83
LV	90	97	87	97	90
Total	417	417	360	100	86

Table4. Kappa coefficien for each class

class	*Kappa coefficient*
WB	1.0000
RD	0.88
IFL	0.87
BL	0.75
BS	0.84
VS	0.95
BLTR	0.83
BCR	0.81
OB	0.81
LV	0.96
Total	0.84

Samples for accuracy evaluation of settlement components were obtained by image sampling and visual interpretation. The accuracy for each settlement component was shown in table5. The Kappa coefficient was calculated for each settlement component, which was shown in table6.

Table5. Accuracy of settlement component

Comp-onent	*test samples*	*labeled*	*true*	*Produc-er Accura c-y*	*User Accur-acy*
BL	23	24	17	74	71
BS	22	23	19	86	83
VS	28	27	23	82	85
BLTR	37	34	30	81	88
BCR	35	36	31	89	86
OB	40	38	32	80	84
VLS	38	41	35	92	85
Total	223	223	187	100	84

Table6. Kappa coefficien for each settlement component

component	*Kappa coefficinet*
BL	0.71
BS	0.85
VS	0.83
BLTR	0.86
BCR	0.86
OB	0.81
VLS	0.90
Total	0.81

The true settlement unit was also extracted by visually interpretation. The true settlement unit was overlain with the settlement unit extracted by the method proposed here and further reformed by expanding and shrinking, which was shown in figure3. The commission area was shown in red and the omitted area was shown in blue in figure3. There were 46 settlement units exactly extracted, 2 settlement unit omitted and 3 settlement unit commissioned. The accuracy of settlement units was 89 percent.

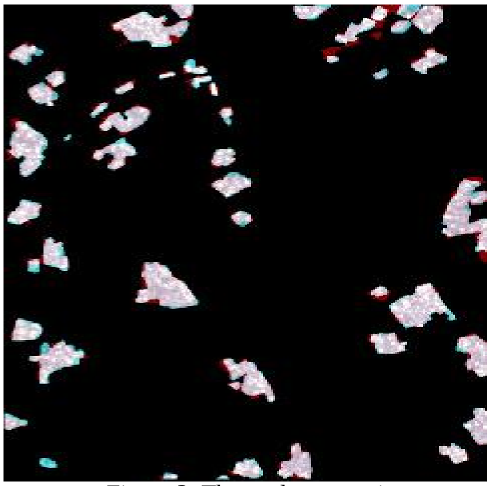

Figure 3. The settlement unit

（The omitted area in blue, commission area in red）

5. CONCLUSION

The rural residnet unit and its component can be exactly extracted from Quickbird satellitte images with the accuracy of respectively 89 and 84 percentage by the methodology proposed here.

ACKNOWLEDGEMENT

The work was supported by LREISF (contract no. A0720), 863 project (contract no.2009AA12Z140), NNSF(contract no. 40771144) and 973 project (contract no. 2009CB421100), and thanks go to Prof. Jiyuan Liu, Chenghu Zhou and Xiaowen Li from CAS, for his kind help.

REFERENCE

C.J.Yang and C.H.Zhou, 2000. Extracting Resident Areas on the TM Imagery. Journal of Remote Sensing, 4(2),pp.146-150.

G.J.Wen,D.R.Li,F.Ye, 2003. Automatic Extraction of Urban Area from Satellite Panchromatic Remote Sensing Images. Editorial Board of Geomatics and Information Science of Wuhan University, 28(2),pp.1671-8860.

H.Y.Pan, M.X.Men,H.Xu and Y.P.Zhou, 2007. Study on Spatial Expansion Pattern of Industrial Land in Tangshan Based on RS and GIS. China Land Science, 21(1), pp.48-52.

J.F.He and D.F.Zhuang, 2006. Analysis of the relationship between urban dynamic change pattern of the Yangtze River Delta and the regional eco-environment. Geographical Research, 25(3),pp.388-395.

J.Y.Li,L.Zhang,B.F.Wu and X.H.Ma, 2007. Study on Extracting Building Density and Floor Area Ratio Based on High Resolution Image. Remote Sensing Technology and Application, 22(3),pp.209-313.

R.H.Ma,W.Chen,X.H.Chen and X.J.Duan, 2004. Town and Construction Land Growth of Changshu City. Acta Geographica Sinic,59(3),pp.418-426.

W.P.Hu,G.Q.Yang,Z.F.Wu and J.B.He, 2003. Studies on recent built-up land-cover change of urban area in the Pearl River Delta. Geographical Research, 22(6),pp.780-788.

X.W.Li, J.Y.Fang, S.L.Piao, 2003. The comparison of spatial characteristics in urban landuse growth among the central and sub-cities in Shanghai Region. Geographical Research, 22(6),pp.69-779.

Y.Zha,S.X.Ni and S.Yang, 2003. An Effective Approach to Automatically Extract Urban Land-use from TM lmagery. Journal of Remote Sensing, 7(1),pp.37-41.