A REMOTE SENSING IMAGE SEGMENTATION METHOD BASED ON SPECTRAL AND STRUCTURE INFORMATION FUSION

Qinling Dai[a] Guoying Liu[b] Cancai Wang[c] Leiguang Wang[*d]

[a] School of Wood Science and Interior Design, Southwest Forestry University, 300 Bailongsi Road, Kunming,Yunnan, China, 650224
[b] College of computer and commmunication engneering, Changsha University of Science & Techology, 76Chiling Road,Changsha, China, 410079
[c] School of Polymer Science and Engineering, Qingdao University of Science & Technology, Zhengzhou Road,Qingdao,Shandong,China,266042
[d] National Laboratory for Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, 129 Luoyu Road, Wuhan, China, 430079

Commission VII, WG VII/6

KEY WORDS: Segmentation, Mean Shift, Information Fusion

ABSTRACT:

The focus of this paper is on the segmentation algorithm for the high resolution multispectral imagery to get regions which are roughly corresponding to land cover types. We propose the combination of spectral features and spatial features by Gabor filter banks and a variable mean shift clustering algorithm in high dimension is employed to achieve feature fusion. Some issues on the measure metric of different features and standilzation are discussed. The whole algorithm is evaluated on the synthetic texture image, which are cropped from a QuickBird image with typical land–cover types. Compared with fixed bandwidth Mean Shift segmentation algorithm, our method has better performance in distinguishing the different land cover types with similar spectral surface.

1. INTRODUCTION

Image segmentation is a very important process in many image vision applications, which involved in partitioning an image into isolated regions, such that each region shares common properties and represents a different object.(Jung,2007).A large collection of literature on image segmentation has been proposed over the past decades. Since image segmentation represents the interface between image pre-processing and image understanding, segmentation algorithms are often application-dependent(Zhang et al.,2007).In our image understanding target, segmentation regions are as a basis for the following image classification mission. It is obvious that the quality of classification is directly affected by segmentation quality, so our segmentation algorithm focuses on partitioning HR multi-spectral remote sensing images into isolated regions which correspond to land-cover classes roughly. Compared with close-range images, the HR or very high resolution (VHR) remote sensing image is very rich in spatial detail and some land cover classes have similar spectral representation, such as glass and tree, road and roof. It means that the conventional spectral features will be inadequate for the VHR imagery segmentation. It seems evident that the VHR images do create additional challenges in terms of information extraction and classification (Dell'Acqua et al.,2004; LeiGuang et al.,2006; Puissant et al.,2005; Xin et al.,2007).

Recently , a unified frame for gray and color image filter and segmentation based on the mean shift (Comaniciu and Meer,2002) presents good results for close-range images and the most important is robust in feature space. In this algorithm, a kernel in the spatial-range joint domain is defined, in which spatial location with 2-dimension and the range feature with image pixels in the CIE Luv color space is filtered, and then filtered pixels are clustered together according to the threshold of the minimum region defined by pixel count. Essentially, image filtering (also called image smoothing) based on mean shift is an instance of gradient ascent with an adaptive step size in joint color-position domain and the segmentation is the combination of seeking the mode of joint density in color-position feature space and merging of modes. One attractive property of image filtering based on mean shift is that the filter result is discontinuity preserving, which means that pixels in a region (mostly belonging to the same land-cover classes) will be smoothed and the variability in the region is deduced, while the boundary between regions has been preserved.

In our remote sensing image segmentation tasks, decomposition of the multispectral image into homogenous tiles is desired, and one tile can correspond to one kind of ground object roughly. So our segmentation tasks are somewhat object-oriented. Considering the spectral similarity of some pairs of ground object, the general fixed-band mean shift based segmentation in (Comaniciu and Meer,2002), which only clusters color or gray level feature in image lattice, is not sufficient to getting desirable segmentation result. The spectral similarity of different land-cover types in HR imagery may lead to the convergence of different classes to the same mode in the spectral feature space. The discrimination performance of spectral feature is further reduced. Considering the

[*] E-mail: corresponding author :wlgbain@gmail.com.

insufficiency of spectral feature in mean shift based HR image segmentation, a Gabor wavelet texture descriptor (Manjunath and Ma,1996) is introduced and the original mean shift clustering method in joint range-spatial domain (Comaniciu and Meer, 2002)is replaced with joint spatial-texture domain.

The remainder of this paper is organized as follows: section2 provides a brief revision on texture feature extraction based on Gabor filter and the spectral feature abstraction. The proposed method is described in section 3, and then experimental results are given in section 4. Conclusions are drawn in section 5.

2. IMAGE SPECTRAL AND SPATIAL FEATURE ABSTRCT TITLE

In the HR imagery, some of the landscape elements are represented by a group of individual pixels, it means that the conventional image interpretation based on pixels will no longer sufficient. The combination of spectral and textural descriptor will provide a promising solution for remote sensing image interpretation (Dong-chen, 1990). The use of Gabor filter as spatial feature is motivated by various reasons. Firstly, The Gabor wavelets, whose kernels are similar to the2-D receptive field profiles of the mammalian cortical simple cells, exhibit strong characteristics of spatial locality and orientation selectivity, and are optimally localized in the space and frequency domains(Chengjun and Wechsler, 2003). Secondly, with a bank of Gabor filters a set of filtered images are produced and one can use simple statistics of gray values in the filtered images as texture features directly. Compared with texture descriptor based on statistics in the window, The Gabor feature may provide small error rate at region localization.

2.1 Multiresolution Gabor Features and Dimension Reduction

A two dimension Gabor mother function ***h(x,y)*** and its Fourier transform ***H(u,v)*** can be written as follows (LeiGuang et al.,2006; Manjunath and Ma,1996):

$$h(x,y)=\exp\left[-\frac{x^2}{2\sigma_x{}^2}-\frac{y^2}{2\sigma_y{}^2}\right]\cos\left(2\pi u_0 x\right) \tag{1}$$

$$\mathrm{H(u,v)}=2\pi\sigma_x\sigma_y\left(\exp\left\{-\frac{1}{2}\left[\frac{\left(u-u_0\right)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\}\right) \tag{2}$$

where $\sigma_u=1/\left(2\pi\sigma_x\right), \sigma_v=1/\left(2\pi\sigma_y\right)$.It is obvious that u_0 is the frequency the sinusoidal wave along the u-axis .A family of Gabor filters $h_{mn}(x,y)$ can be obtained by scaling and rotation of $h(x,y)$:

$$h_{mn}(x,y)=a^{-m}g(x',y') \qquad a>1, m,n\in Z \tag{3}$$

by $x'=x\cos\theta+y\sin\theta$, $y'=y\cos\theta-x\sin\theta$

where $\theta=n\pi/orienations\_total$ is called orientation parameter and m is scale factor.

In paper (Manjunath and Ma,1996), a filter bank design strategy to make the half-peak magnitude support of Gabor filter responses in the frequency spectrum touch each other is proposed and a series filtering results corresponding to the multi-scale frequency response and having the same spatial size as the original image are obtained. In our method, this strategy is employed. The lower and upper centre frequency of interest, number of stage and orientation should be predetermined in the algorithm. In our experiments, the number of stage and orientation is chosen as 4 and 6, the lower and upper centre frequency is 0.05 and 0.4 empirically, considering the trade off between computation efficiency and the overall performance. Even though, there are $3\times4\times6$ dimensions Gabor features for a HVR image with three bands, PCA(Principle Component Analysis) (Sa, 2001) is used to reduce feature further and retain principle components(PC) till an cumulative eigenvalue threshold reached. In our paper, the threshold is 0.98 and about half of PCs is discarded.

2.2 Spectral Information

In most cases, a single texture measure cannot provide enough information on ground object discrimination. Better segmentation result should be desired by considering multi-feature fusion. Obviously, the spectral feature in HR multi spectral imagery is complementary with the Gabor feature providing texture or structure information.

Generally speaking, Color spaces used for image processing purposes should have color discrimination properties which are comparable to those of the human visual system.But unfortunately, the color error in RGB color space is not perceptually uniform and the same Euclidean distances in different position of RGB gamut don’t correspond to the same perceived color differences. The Lab color space is another color space which is designed to approximate human vision. It aspires to perceptual uniformity and a available conversion formulae from RGB space to Lab space can be find in . So in our experiments, the spectral feature in Lab color space is employed.

3. JOINT DOMAIN VARIABLE BANDWIDTH MEAN SHIFT SEGMENTATIN

In this part, a segmentation frame based on adaptive bandwidth Mean Shift and some implementation detail is discussed.

3.1 Adaptive Bandwidth Mean Shift

Given n data points set $X=\{x_i \mid i=1,2....n\}$ in ***d*** dimension space $\boldsymbol{R^d}$, let ***f(x)*** be the probability density in feature space, then ***f(x)*** can be estimated by multivariate kernel density estimator (known as the Parzen window estimator)(Comaniciu and Meer, 2002) with kernel ***K(x)*** and a symmetric positive $d\times d$ bandwidth matrix ***H*** and given as follow:

$$\hat{f}(x)=\frac{\sum_{i=1}^{n}K_H\left(x_i-x\right)}{n} \tag{4}$$

where $K_H(x) = |H|^{-1/2} K(H^{-1/2}x)$ (5)

Considering the complexity of the estimation, the bandwidth matrix H in (5) is usually chosen as proportional to the identity matrix $H = h^2 I$, and then only one bandwidth h must be provided. The kernel density estimator can be expressed as (6).

$$\hat{f}(x) = \sum_{i=1}^{n} \frac{1}{nh^d} K\left(\frac{x_i - x}{h}\right) \tag{6}$$

Kernel ***K(x)*** is a class of bounded functions satisfying some conditions(Comaniciu and Meer, 2002; M.P.Wand and M.C.Jones, 1995) and a special function ***k(x)*** called profile function is defined satisfying

$$K(x) \equiv C_k k(\|x\|^2) \tag{7}$$

Where C_k is normalization positive constant which makes ***K(x)*** integrate to 1.

When a constant bandwidth *h* in formulae (6) is extended to a bandwidth function $h(x_i)$ (h_i for short) associated with the sample point x_i, an adaptive sample point estimator is got (8).

$$\hat{f}(x) = \sum_{i=1}^{n} \frac{1}{nh(x_i)^d} K\left(\frac{x_i - x}{h_i}\right) \tag{8}$$

For *profile function* $k(x)$, if $k'(x)$ exists for all $x \in [0, \infty)$, define $g(x) \equiv -k'(x)$, and kernel $G(x) \equiv C_G g(\|x\|^2)$.

Then the density gradient estimator of (8)is obtained:

$$\hat{\nabla} f_K(x) = C\left[\frac{\sum_{i=1}^{n} G\left(\frac{x_i - x}{h_i}\right)}{nh_i^{\,d}}\right]\left[\frac{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} x_i g\left(\left\|\frac{x_i - x}{h_i}\right\|^2\right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\|\frac{x_i - x}{h_i}\right\|^2\right)} - x\right] \tag{9}$$

The density estimator of x with kernel G, noted as $\hat{f}_G(x)$. The second square bracket term is the difference between the weighted mean of data points fallen in the bandwidth range of kernel and the center if the kernel x, noted with $m_{h,G}$, called the mean shift vector.

$$m_{h,G} \equiv \frac{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} x_i g\left(\left\|\frac{x_i - x}{h_i}\right\|^2\right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\|\frac{x_i - x}{h_i}\right\|^2\right)} - x \tag{10}$$

From (10), (9) becomes

$$m_{h,G}(x) = \frac{1}{2} h^2 C \frac{\nabla \hat{f}_K(x)}{\hat{f}_G(x)} \tag{11}$$

The expression (11) illustrates that, at location x, the mean shift vector evaluated with kernel ***G*** is proportional to the density gradient estimate obtained with kernel ***K*** (Comaniciu and Meer,2002; Ozertem et al.,2008) and when $m_{h,G}(x) \to 0$, $\nabla \hat{f}_K(x) \to 0$ .So the mean shift vector always points toward the direction of maximum increase in the density, finding the point where the estimate $\nabla \hat{f}_K(x) = 0$ is equal to finding the root of $m_{h,G} = 0$.According to (10), an iteration formulation can be given:

$$y_{j+1} = \frac{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} x_i g\left(\left\|\frac{x_i - y_j}{h_i}\right\|^2\right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}} g\left(\left\|\frac{x_i - y_j}{h_i}\right\|^2\right)} \qquad j = 1, 2, \cdots \tag{12}$$

When the kernel K has a convex and monotonically decreasing profile, it can be proved that the sequences $\{y_j\}_{j=1,2....}$ converge, and the proof is given in the literature (Comaniciu and Meer,2002; Zhi ,W., and Zi,C.2007; Xiang ,L. et al.,2005). It also has been proved that the introduction of variable bandwidth function doesn’t change the convergence of Mean shift iteration. The detail proof can be found in the APPENDIX section of (Comaniciu et al.,2001). It is more important that a variable bandwidth mean shift algorithm with pilot density estimate has shown its superiority over the fixed bandwidth procedure(Comaniciu et al.,2001; Georgescu et al.).

In our segmentation algorithm, a pilot density estimate via nearest neighbours as used in (Georgescu et al.)is employed. Let $x_{i,k}$ be the k-nearest neighbour of the central point x_i, the L_1 norm is used as distance metric and the distance is taken as the band width $\boldsymbol{h_i}$ of $\boldsymbol{x_i}$. Now, we can get a practical algorithm for mean shift iteration.

Let $\boldsymbol{x_i}$ and $\boldsymbol{z_i}$ be the $\boldsymbol{d}$-dimensional input and filtered result of $\boldsymbol{x_i}$, $\boldsymbol{n}$ is the number of pixels. Mean Shift based image segmentation algorithm can be described as follows:

```
For i = 1:n
Estimate h_i ;
End

For i = 1:n
Initialize j=1 and y_{i,1} = x_i ;
Compute y_{i,j+1} iterative using (12) until convergence;
z_i = y_{i,j+1} ;
End
K-means for finally segmentation result
```

3.2 Mean Shift Segmentation Implementation in High Dimension Feature Space

In our method, original fixed-bandwidth Mean Shift algorithm is replaced by a variable-bandwidth technology in (Georgescu et al.) which is suitable for the segmentation task in high-dimension features.

Spectral feature in Lab color space with 3 dimensions and PCs got from Gabor features corresponding to different stages and orientations of image frequency domain are combined together to consist of feature space. However, even about a half of PCs of Gabor features is reduced; there are about 35 Gabor features should be preserved to maintain the balance between performance and processing time for a 3 bands multispectral Quickbird image using a Gabor filter banks with 4 stages and 6 orientations.

In practise, the Mean Shift iteration of (12) require a neighbourhood query, it is obviously impractical by scanning the whole feature space in such high dimension space, considering the high complexity of the mean shift algorithm $\boldsymbol{O(Ndn^2)}$,where N is a average iteration times for one point. In order to improve the efficiency of the neighbourhood query, a data structure named locality- sensitive hashing(LSH) is used in (Georgescu et al.). Limited by the space, here we only give a brief review on it.

The basic idea of LSH is to hash the input data so that similar items are mapped to the same buckets with high probability. The algorithm has two main parameters: the width parameter *k* and the number of hash tables *L*. Firstly, a family of hash functions H is defined; and then *L* group hash functions *g* is obtained by concatenating *k* randomly chosen hash functions *L* times from set H. In other words, the algorithm constructs *L* hash tables, each corresponding to a different randomly chosen hash function *g* and *g* is consisted with *k* randomly chosen hash functions in H.

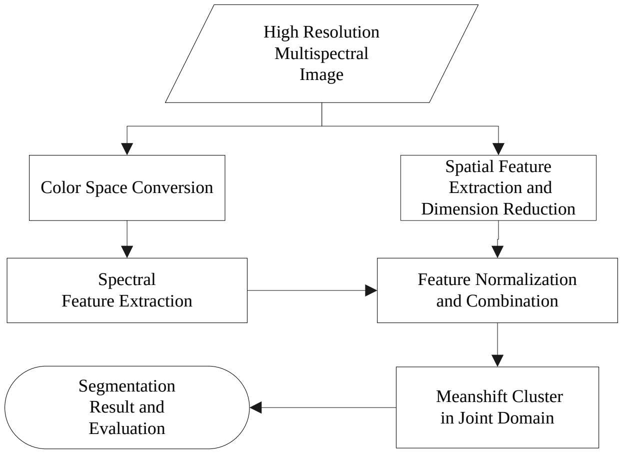


Figure.1 The flow chart of our segmentation technology

Now, a segmentation flow chart is given. Firstly, HR multi-spectral image with RGB bands is filtered by Gabor filter banks respectively and the dimension of spatial features is reduced by PCA. On another way, 3-dimensional spectral features obtained by converting pixel values in RGB color space to Lab. It is evident that the measure unit of feature has great influence on the clustering, The usual form of equalizing the feature contribution consists of performing some scaling operation(Sa,2001),section2.3.However, it is almost impossible to devise a suitable standardization method , since we don't know beforehand the type of the clusters we are dealing with. One feasible way is "trial and error" approach. In our experiment, each dimension of Gabor features is normalized by scaling into the range [0 1], and scale Lab color space data by multiplying a constant 4/125. After pre-processing of image feature, the adaptive Bandwidth Mean Shift smoothing portrayed in the secition3.1 is executed in the joint feature space. Finally, segmentation results are analysized.

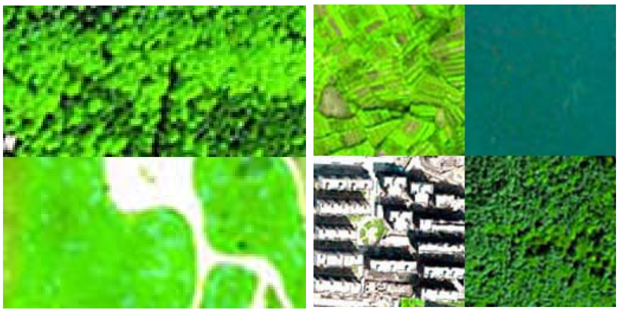
4. EXPERIMENTS RESULTS

4.1 Experiment Images and Algorithm Parameters

In this part, some experiments have been conducted to illustrate the effectiveness of the proposed method. In the experiments, test images with RGB three bands are cropped from a QuickBird imagery of Wuhan, China. As shown in follow Figure 2, the first image consists of three typical land cover types: naked land, grass and tree. It is obvious that the tree is very close with grass in spectral information. The second image consists of five classes, that is, water body, farm land, tree, building and shadow.

As mentioned in Section 3, there are 7 parameters used in the proposed segmentation method. In Gabor filter banks design stage, the centre frequency rang of interest and the scale and orientations parameter are needed. In our experiment, we found that the default set of parameters in (Manjunath and Ma,1996) can meet ore demand on efficiency and performance. [0.04 0.5] is set to frequency center rang and 4 scales and 6 directions is chosen. For PCA, the contribution threshold used for preserving principle components is 0.98. In hashing the high dimension set stage, L and K parameters described in section 3.2 for the first image are 2 and 28. Finally, the number of class in image, the first is 3, the second is five.

In addition, the different classes are labeled randomly since we use K-means for final result; it means that even the same land-cover types in different result images must be labeled differently. So we judge the performance of results by comparing with the original image directly.

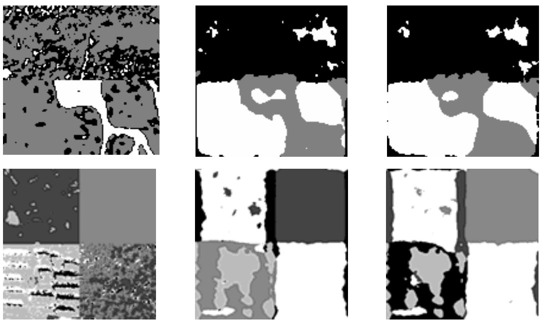


a. synthetics texture1 b. synthetics texture2

Figure 2. Two texture images synthesized from the same QucikBird image of Wuhan, China. And each raster band has been qualified into 256 gray levels. The size of the first one is 128×128.the second is 256×256.

4.2 Experiment 1

To validate the differentiate power of features used in the algorithm; the performance of individual spectral features, all Gabor PCs features and the retained PCs are represented. In those experiments, each feature set is put into K-means classifier directly; classification results for both images are shown in the Figure 3.



a. b. c.

Figure 3 K-means segmentation results of two images. The first column uses Lab color, the second use all Gabor PCs features; the third uses a part of PCs which is determined by contribution threshold 0.98(described in section 2.1)

From the first column, we can find the spectral information performed well when the great spectral difference exists in between classes and the result has good discontinuity preserving performance. However, the grass and tree in the first image, farm land and tree are mixed due to their similarity in spectral information. On the contrary, Gabor feature provide better regional information, but weak boundary. In addition, by comparing the second and the third column, it is obviously that the performance of Gabor feature doesn't reduce significantly with the reduction of number of Principle Components in some degree. From the result, we can conclude the Lab color and Gabor feature may provide us some complementary information about the HR imagery. In the next section the potential of spectral and spatial feature fusion will be evaluated.

4.3 Experiment 2

In this part, the combination of spatial and spectral information with different scales is compared (as shown in Figure 4).

From the first column, we can find that spectral feature seems to play a dominant role in segmentation since the tree and grass pair in the upper image, farm land and tree pair in the lower are similar in the spectral surface and classes mixed together. Fundamentally, it caused by the different nature of the features, which are measured in different measurement units and occupying quite disparate value ranges. In order to get a balanced contribution of all features to classification and preserve semantic information, a simple scale factor is chosen. The segmentation result with standardized data is shown in the second column. Compared with the first, the confusion of different land cover classes is reduced, especially for the upper one.

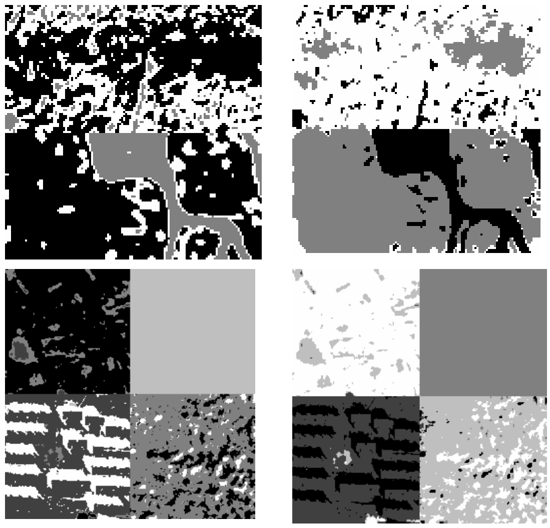


Figure 4. The k-means results using combinations of two type of feature with different scales. The first column, feature is combined without any scale change. The second column, Lab feature is scaled by multiplying a constant 4/125; and Gabor PCs is mapped linearly into range [0 1].

4.4 Experiment 3

In this part, our algorithm compared with a fixed bandwidth mean shift segmentation in (Comaniciu and Meer, 2002) with default parameters..

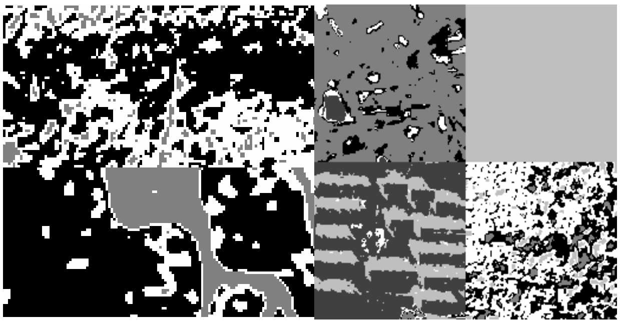


Figure 5..Result using algorithm in (Comaniciu and Meer, 2002) with default parameter.

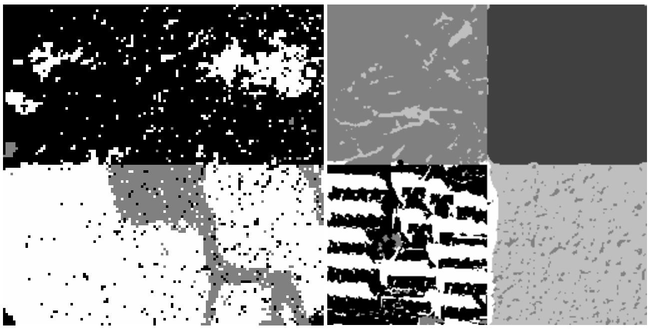


Figure 6. The result of our method

Figure 6 is segmentation result using our method。Figure 5 is the result from EDSION softer ware implementing the algorithm in the paper (Comaniciu and Meer, 2002), which is a combination of fixed band Mean Shift filtering and region merging. To keep the equality of comparison, only the fixed Mean Shift filtering procedure is employed with default parameter spatial band 7 and rang band 6.5. Then filtering result is segmented into several classes by K-means method. From the Comparison of Figure 6 and Figure 5, we can find that the fixed bandwidth method confused the land cover types with similar spectral information. In figure6, the confusion of classes similar in spectral information is reduced in some degree. In fact, only by a simple religion merging algorithm to merging the region whose pixels is less a threshed, for example 20.a better result can be achieved.(as shown in Figure 7)

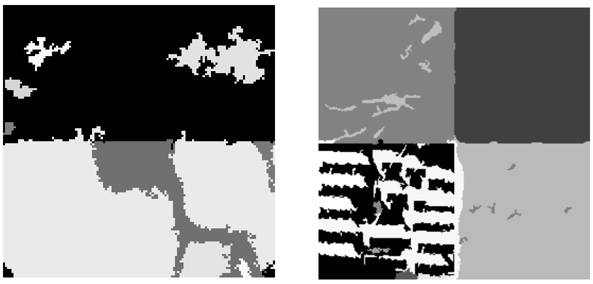


Figure 7 the result with merging minimum region

5. CONCLUSION

A segmentation algorithm based on spatial and spectral information fusion is proposed in this paper. The algorithm leads to an improvement in segmentation of land cover classes having similar spectral surface.

ACKNOWLEDGEMENTS

This work was supported by the 973 program and 863 program of People's Republic of China under Grant 2006CB701303 and 2006AA12Z132, the Foundation of the excellent State Key Laboratory under Grant 40523005, and the National Nature Science Foundation of China under Grant 40601055,the foundation of post-doctor of China under Grant 20060390825.

REFERENCES

Wikipedia,2007 Lab color space conversion. http://en.wikipedia.org/wiki/Lab_color_space (Accessed 28 March.2008)

Chengjun, L. and Wechsler, H.,2003. Independent component analysis of Gabor features for face recognition. Neural Networks, IEEE Transactions on, 14(4): 919-928.

Comaniciu, D. and Meer, P.,2002. Mean shift: a robust approach toward feature space analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(5): 17.

Comaniciu, D., Ramesh, V. and Meer, P.,2001. The Variable Bandwidth Mean Shift and Data-Driven Scale Selection, Proceeding of the IEEE international on Computer Vision, Canada.

Dell'Acqua, F. et al.,2004. Exploiting spectral and spatial information in hyperspectral urban data with high resolution. Geoscience and Remote Sensing Letters, IEEE, 1(4): 322-326.

Dong-chen, H.,1990. Texture Unit, Texture Spectrum, And Texture Analysis. Geoscience and Remote Sensing, IEEE Transactions on, 28(4): 509-512.

Georgescu, B., Shimshoni, I. and Meer, P.,2003. Mean Shift Based Clustering in High Dimensions:A Texture Classification Example, the Ninth IEEE International Conference on Computer Vision.

Jung, C.R.,2007. Unsupervised multiscale segmentation of color images. Pattern Recognition Letters, 28(4): 523-533.

LeiGuang, W., Wenbo, W., QinLing, D. and Qianqing, Q.,2006. Remote sensing image texture classification based on Gabor wavelet and support vector machine, SPIE.

M.P.Wand and M.C.Jones,1995. Kernel Smoothing. Chapman and Hall.

Manjunath, B.S. and Ma, W.Y.,1996. Texture features for browsing and retrieval of image data. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 18(8): 837-842.

Ozertem, U., Erdogmus, D. and Jenssen, R.,2008. Mean shift spectral clustering. Pattern Recognition, 41(6): 1924-1938.

Puissant, A., Hirsch, J. and Weber, C.,2005. The utility of texture analysis to improve per-pixel classification for high to very high spatial resolution imagery. Taylor & Francis, pp. 733 - 745.

Sa, J.P.M.d.,2001. Pattern Recognition: Concepts, Methods and Applications. Springer.

Wang, L., Wu, W., Dai, Q. and Qin, Q.,2006. Remote Sensing image texture classification based on Gabor wavelet and support vector machine, IGARSS2006, Proc. of IEEE, Wuhan .China.

Xin, H., Liangpei, Z. and Pingxiang, L.,2007. An Adaptive Multiscale Information Fusion Approach for Feature Extraction and Classification of IKONOS Multispectral Imagery Over Urban Areas. Geoscience and Remote Sensing Letters, IEEE, 4(4): 654-658.

Xiang ,L., Fu,W., Zan,W,H,2007.Convergence Analysis of Mean Shift Algorithm Journal of Software., 16(3): 10. (in chinese)

Zhang, H., Fritts, J.E. and Goldman, S.A.,2007. Image segmentation evaluation: A survey of unsupervised methods. Computer Vision and Image Understanding, In Press, Corrected Proof: 175.

Zhi ,W., Zi,C.,2007.Convergence Analysis of Mean Shift Algorithm Journal of Software., 18(2):8 (in chinese)