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High-resolution Remote Sensing Image Classification based on Adaptive Bandwidth with Mean Drift Method

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Abstract

In this paper, based on the image element shape index, we introduce the object-oriented idea and improve the mean drift method with adaptive bandwidth to extract images with high spatial resolution, and the classification results obtained by using this method show that it is better than the image element shape index method in terms of accuracy and visual effect, which makes the image extraction better.

Keywords

Mean Drift; High-resolution Images; Extraction Accuracy; Object-oriented.

1. Introduction

About high spatial resolution remote sensing image feature extraction, more research needles are based on shape, geometric structure and other spatial features. Compared with texture features, the shape and geometric structure features of high spatial resolution remote sensing images are richer and can describe the attributes of the target in more detail, which achieves better classification effect and improves the classification accuracy. Based on the mean drift method, which is a statistical iterative algorithm based on nonparametric probability density estimation, this paper uses the research basis of the image element shape index method and adopts a bandwidth adaptive selection mean drift method to change the minimum primitive of the image from image element to object [1] for classification, which is compared with the image element-oriented method.

2. Object-oriented idea

Whether the spectral feature classification based on support vector machine or PSI method or other feature extraction methods, all of them are an image classification method oriented to image elements. With the increasing spatial resolution of remote sensing images, the images have a large number of pure pixels, and the increase of pure pixels helps to describe the detailed features of the target at a smaller scale on the one hand, and brings a problem that the features of a single pixel can no longer fully express the target on the other hand [2]. That is, in a sense the impact of reducing the local resolution in order to ignore the detailed information of the features. In view of this, object-oriented classification methods have emerged.

Compared with the above element-oriented classification methods, the object-oriented classification method differs from its biggest one in that it takes the object as the smallest unit of image feature

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extraction and analysis, and this difference determines that the object-oriented classification method should first do the extraction of the object. In essence, object extraction is to form a collection of image elements by clustering image elements with similar attributes or several attributes at a certain scale, and these collections are objects.

3. MS Method

3.1 MS vectors

Suppose there exists a d-dimensional feature space R^d,x_i(i=1,2,....n) is the basic form of the MS vector of any one of the n sample points x in the feature space R^d

$$M_h(x) = \frac{1}{s}\sum_{x_i \in S_h}(x_i - x) \tag{1}$$

$$S_h(x) = \{x_i : (x_i - x)^T(x_i - x) \le h^2\} \tag{2}$$

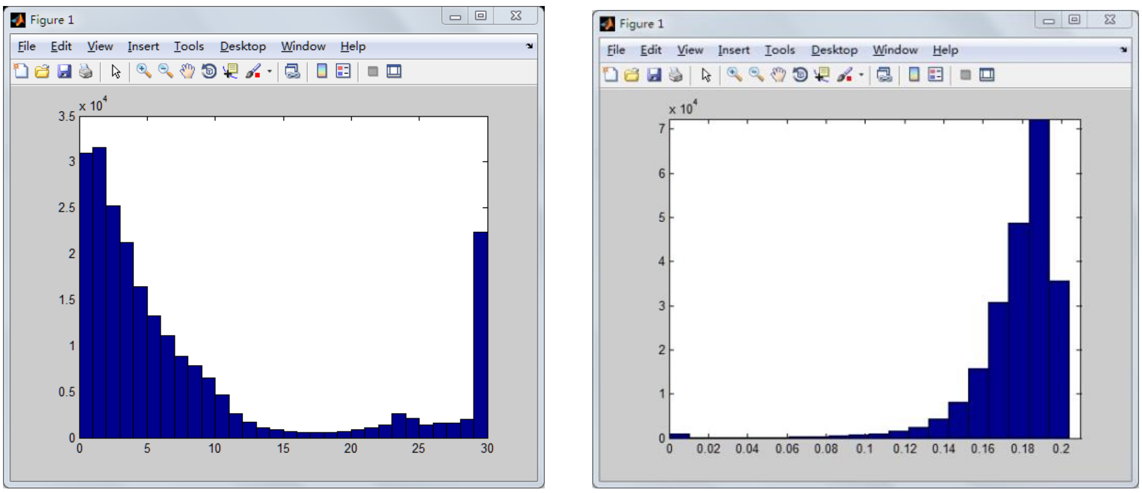
That is, the MS vector represents the difference between the weighted mean value of the sample point x falling into the d-dimensional sphere with x_i as the center and h as the radius and the point x at the center of the sphere.

3.2 MS clustering method

The MS vector can be calculated by equation (2.5), and the iterative method is used to find the place where the probability density is extremely large. The iterative formula for the termination of the iteration is set as the MS vector is less than a very small threshold ε, which means that when the MS vector is extremely small the initial sample point x_i drifts to the place where the local probability density is extremely large, which can also be called the convergence point. Through the above iterative process, the drift path of each sample point x_i can be obtained, noted as $\{y_j\}_i$,i=1,2……n,j=1,2,…. At this time, the end of the drift path, i.e., the convergence point, has been associated with each sample point x_i. The convergence point is used as the center of clustering, so that the sample points with close convergence points belong to the same class.

4. Adaptive Bandwidth MS Approach

The MS method with adaptive bandwidth, which uses bandwidth as a variable, discards the traditional single bandwidth that can be disturbed by detailed information, and its ability to adapt to local changes and constantly modify the bandwidth parameters. The method satisfies two principles: (1) clustering at small scales; (2) clustering at larger scales, able to ignore excessive detail information and avoid interference caused by classification. The method obtained by combining the P-image element shape index method on top of the two.



hs hr

Fig. 1 Histogram of spatial bandwidth (hs) vs. spectral bandwidth (hr)

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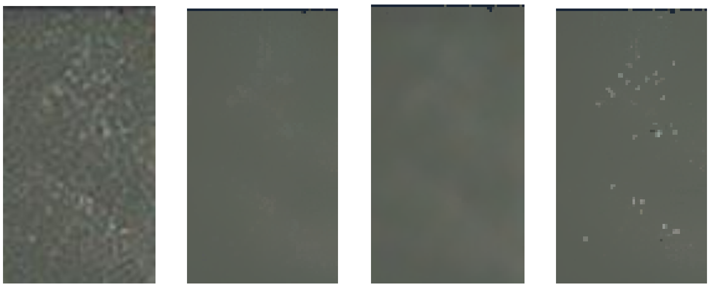
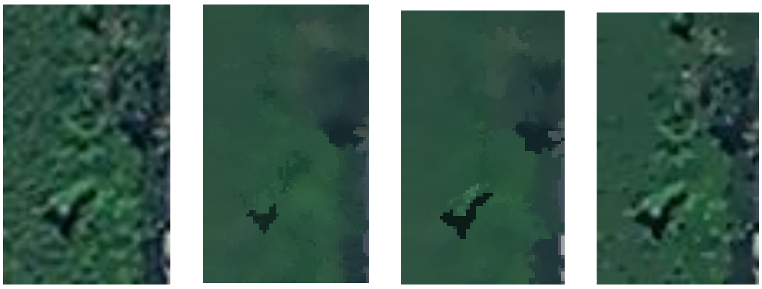
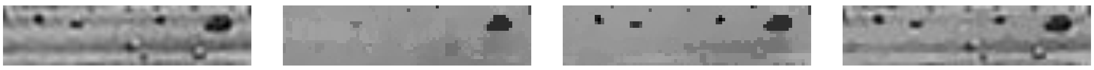
This adaptive bandwidth method optimizes the clustering process of the mean drift method, and from the results, this method ensures sufficient smoothing for larger targets while preserving smaller targets, or larger targets are not over-segmented, while excessive detail information is ignored by over-smoothing. It can be seen that this adaptive bandwidth MS method is a multi-scale object extraction technique, which is more reasonable than the single-scale object extraction.



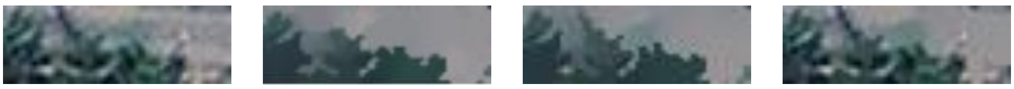
a water



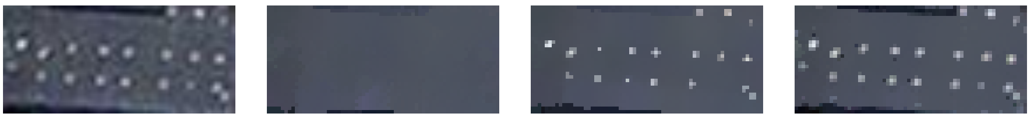
b vagetion



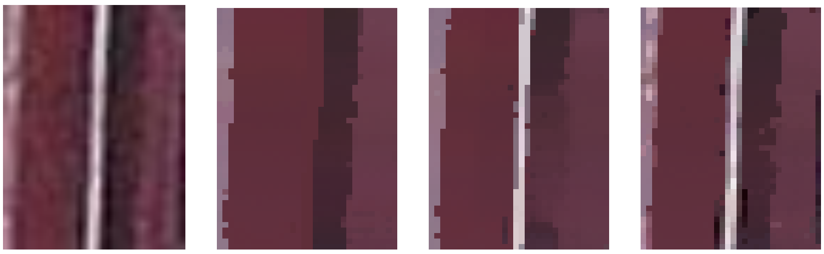
c1 road



c2 road



d1 Building



d2 Building

Raw images, adaptive bandwidth MS method clustering results, hs=8 hr=0.2, hs=4 hr=0.1

Fig. 2 Effect of different object classification

5. Experimental data processing

According to the adaptive bandwidth MS method for clustering experimental images, the spatial and spectral bandwidths were first determined by PSI features. the values of PSI parameters were set as

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D=20, T1=60, T2=60, and the bandwidth of less than 2 was set as the detail information, the bandwidth was set as 3, and the spectral bandwidth was 0.8, and 8 and 0.2, 4 and 0.1 were taken for comparison groups. The histogram of spatial bandwidth (hs) versus spectral bandwidth (hr) is obtained as follows:

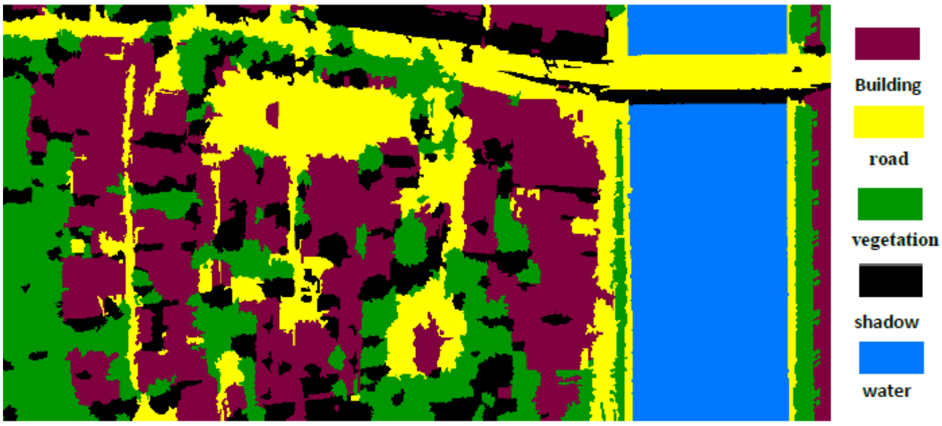
Compare the object extraction results of the three clustering results, as shown in figure 2.

It can be found that the adaptive-bandwidth MS method achieves better clustering results than the fixed-bandwidth MS method, achieving the neglect of excessive detail information as well as more accurate clustering. Following that, the image elements with closer convergence points are merged to obtain a series of point sets, and these point sets are used as objects, and the smaller objects with less than 10 image elements are merged to obtain the object profile shown in the figure below.

Fig. 3 MS mean drift processing results graph

6. Experimental results

The extraction results of the mean shift method based on the improved adaptive bandwidth are as follows, and the classification accuracy achieved using the object-oriented classification method is 91.6%, and the specific computer processing is no longer listed as follows.



Classification accuracy =91.6%

Fig. 4 Object-oriented classification results

It can be found that the classification method combined with the object-oriented idea ignores the excessive detail information well, and does not have the pretzel noise phenomenon existing in the image-oriented classification results, and retains most of the smaller targets, especially the finer roads in the buildings on the left side of the image and the grass on the left bank of the river are well recognized, and the confusion between buildings and concrete roads is reduced to some extent by the geometric shape features. A better classification effect was achieved.

However, the features used to describe the objects in the experiment are fewer and coarser, which means that the targets cannot be distinguished from multiple angles, mainly in the overlap of some buildings and vegetation features with shadows, resulting in classification errors.

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References

[1] Shen Zhanfeng, Luo Jiancheng, Hu Xiaodong, et al. Research on multi-scale mean drift segmentation algorithm for high-resolution remote sensing images[J]. Journal of Wuhan University (Information Science Edition), 2010, 35(3) :313-316.

[2] Comaniciu D, Meer P. Mean Shift: a Robust Approach Toward Feature Space Analysis[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002, 24(5) :603-619.

[3] Wang, Lei-Guang, Zheng, Chen, Lin, Li-Yu, et al. A fast segmentation method based on multiscale mean drift for high-resolution remote sensing images[J]. Spectroscopy and Spectral Analysis, 2011, 31(1): 177-183.

[4] Tan Dongning, Tan Donghan. Small sample machine learning theory: Statistical learning theory [J].Journal of Nanjing University of Science and Technology, 2001, 25(1) :108-112.

[5] YU Hui, ZHAO Hui. New Research on Multi-class Classification Algorithm of Support Vector Machines [J]. Computer Engineering and Applications, 2008, 44(7) :185-189,212.

[6] Burges C J C. A Tutorial on Support Vector Machines for Pattern Recognition[J]. Data Mining and Knowledge Discovery, 1998, 2(2) :121-167.

[7] Chapelle O, Vapnik V. Choosing Multiple Parameters for Support Vector Machines[J]. Machine Learning, 2002, 46(1-3) :131-159.

[8] DING Shifei, QI Bingjuan, TAN Hongyan. Review on Theory and Algorithm of Support Vector Machines [J]. Journal of University of Electronic Science and Technology of China, 2011, 40(1) :2-10.

[9] Zhang Rui, Ma Jianwen. New progress of support vector machine application in remote sensing data classification [J].Advances in Earth Sciences, 2009, 24(5) :555-562.

[10] Dixon B, Candade N. Multispectral Landuse Classification using Neural Networks and Support Vector Machines: One or the Other or Both?[J]. International Journal of Remote Sensing, 2008, 29(4):1185-1206.

[11] Mathur A, Foody G M. Multiclass and Binary SVM Classification: Implications for Training and Classification Users[J]. IEEE Geo-science and Remote Sensing Letters, 2008 5(2) :241-245.