HIGH RESOLUTION REMOTE SENSING IMAGE SEGMENTATION BASED ON MULTI-FEATURES FUSION

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Abstract:

High resolution remote sensing images contain richer information of spatial relation in ground objects than low resolution ones, which can help describe the geometric information and extract the essential features more efficiently. However, the handling difficulties due to the relative poorer spectral information, represented by phenomena of different objects with the same spectrum and the same object with the different spectrum, may cause the spectrum-based methods to fail. Besides, the inherent geometric growth in processing of traditional methods caused by growing pixels always leads to longer processing time, poorer precision, and lower efficiency. Combining the spectral features with textural and geometric features, we proposed a novel kernel clustering algorithm to segment high resolution remote sensing images. The experimental results were compared with mean shift and watershed algorithms, which validated the effectiveness and reliability of the proposed algorithm.

1 Introduction

Remote sensing is a technology of obtaining the surficial information of the earth without contacting, which can determine the locations, characters, properties and change rules of the ground targets by detecting and recording the electromagnetic radiation information of ground targets for subsequent processing, analysis and application [1].

After launching meter-level sensors represented by IKONOS (1999), QuickBird (2001) and OrbView (2003), and launching sub-meter-level sensors represented by WorldView-1 (2007), the commercial applications of high resolution remote sensing images come into an unprecedented prosperous stage. Compared with the traditional low resolution remote sensing images, the high resolution ones contain richer spatial information, such as spectral, textural and geometric features, for which reason it has become one of hotspots in the research of the remote sensing technology [2]. However, the handling difficulties caused by the relative poorer spectral information, represented by phenomena of different objects with the same spectrum and the same object with the different spectrum [3, 4], make the spectrum-based methods fail. Besides, the inherent geometric growth in processing of

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traditional methods caused by growing pixels always leads to longer processing time, poorer precision, and lower efficiency. Combining the spectral features with textural and geometric features, we proposed a novel kernel clustering algorithm to segment high resolution remote sensing images. The experimental results were compared with mean shift and watershed algorithms, which validated the effectiveness and reliability of the proposed algorithm.

The rest of this paper is organized as follows. Section 2 provides an overview on the methods of Remote Sensing Image Segmentation. Kernel Clustering problem is discussed in Section 3. Section 4 proposes the multi features-based remote image segmentation algorithm in detail. Section 5 conducts the experimental results on both synthetic and real-world data set, and Section 6 ends this paper with a conclusion.

2 Remote sensing image segmentation

Remote sensing image segmentation is a major research topic of remote sensing image processing, which partitions images into different areas according to some criteria for more meaningful descriptions, or for subsequent analysis and applications [5].

Compared with the ordinary ones, remote sensing images have some unique features, for example, more grey degree levels, more informative, fuzzy regional boundaries, and more complexity on the structure of the target. The entire features make the remote sensing image segmentation not only difficult to be a fully reliable model for guidance, but also the related research works are challenging.

According to different strategies adopted in handling methods, remote sensing image segmentation can be divided into categories as follows.

2.1 Gray level threshold-based segmentation

According to different grayscale distribution, this method can divide images into two parts, the target and the background. The theoretical hypothesis is that, both of the pixels of target and background in an image are unimodal distribution, where the pixels under the same modality are highly correlated, and the pixels under different modalities are highly uncorrelated.

The key technique chooses a reasonable and appropriate grayscale threshold, which always determines whether or not the segmented results are favorable. If the gray level difference between different classes is large enough, the setting of threshold value will be easy, and the segmentation results tend to be satisfactory. But if the grayscales of different classes are highly mixed up, it will be hard to set the threshold, and the segmentation results tend to be dissatisfactory. Unfortunately, the situation of highly mixed up grayscale is very common in the field of remote sensing image segmentation. At the same time, the gray level threshold-based method cannot make the full use of multi-band observation information of remote sensing image, which results in the failure to be directly applied to the remote sensing image segmentation.

2.2 Edge detection-based segmentation

Edge refers to the transition area between target and background, which is the most distinctive feature of image. Edge detection-based segmentation methods segment images by detecting the boundary points and putting them together to constitute a complete border, where pixels usually change in roof-like or even step-like way [6].

The key technique is called edge detection operator, which calculates the differences of each pixel's neighborhood in different directions, and then determines the changing directions according to the difference in different directions [7]. The frequently-used edge detection operator can be listed as follows. Roberts operator, Laplace operator, Prewitt operator, Sobel operator, Robinson operator, Canny operator and Kirsch operator [8, 9]. Common edge detection-based segmentation includes the edge image threshold method, the edge relaxation method, the boundary tracking method, Hough transform method and edge detection method based on boundary location information, etc.

The edge detection-based segmentation has obvious advantages in extracting targets with significant edges in image. However, the high resolution remote sensing images are usually complex distributed images/systems, for example, pixels within the same target also have obvious edges, but edges between different targets may not be obvious. For these cases, the segmentation results inevitably fall into over-segmentation. In addition, the edge detection-based method, cannot guarantee the regional connectivity, which will result in inconvenience for subsequent image analysis and interpretation.

2.3 Region-based segmentation

According to the same or similar characters of image pixels, the region-based segmentation can connect the neighboring pixels to achieve image segmentation. It can be divided into region growing method and region splitting and merging method, both of which can make a full use of space information and the correlation between pixels. However, some priori information will be required at the same time, such as the seed pixel and a variety of criteria to define the target boundaries, which are difficult to be acquired in some cases.

1) Region growing method

Region growing method, initializes from several seed points or seed regions, according to certain growth standards, discriminates and connects the points of neighborhood pixels until all pixel points have been connected [10-12]. This method determines two key elements, the seed point and the growth standard, which leads to the subjectivity in the selection of the corresponding values. Besides, the phenomenon of the same object with different spectra for high resolution images is serious, which results in the failure of generating complete ground objects in practical applications.

2) Region splitting and merging method

Region splitting and a merging method are just on the opposite sides of a region growing method. Its basic idea is firstly splitting the image into multiple regions according to certain principles, and then iteratively splitting and merging until meets the requirements of forming region. The initial segmentation results can be generally unoverlapped areas of any size. But different initial segmentation structure may lead to different final result, namely the algorithm is instable. The main difficulties arising here are to do with choosing the appropriate division of initial regions, but also with splitting and merging principles. Besides, the method requires an algorithm for calculating complex operations.

The most representative method called watershed segmentation [13-16], based on gradient and the advantage is that it can get one pixel wide which can result in a closed connected precise outline. However, it is difficult to select a proper label in watershed segmentation method so that improper labeling always leads to an over-segmentation result.

2.4 Texture-based segmentation

Any kind of surface has its own inherent texture. As one of the essential characteristics of the image, texture can be used to fully express the surface information of object in detail. It is regularly on the macroscopic, but irregularly on the microscopic scale. Due to the complexity and uncertainty in texture, the texture-based segmentation method always belongs to supervised learning. The common texture can be divided into texture of space and frequency domains, where the most used in the texture of space domain is gray level co-occurrence matrix, and the most used in the texture of frequency domain is the Gabor Filter.

The texture-based segmentation method is valid for the low resolution images. However, for the high resolution images, the inconsistency of internal texture in the same ground object, and a huge amount of calculation, both of which result in the failure of handling high resolution remote sensing image segmentation.

2.5 Clustering-based segmentation

The clustering-based segmentation methods [17-19] represent the pixels in the image space with the corresponding feature space points, segment the feature space points according to their clustering in feature space, and then map them back to the original image space to achieve the segmentation results.

These methods can be classified into two categories, multi-dimensional clustering and multi-dimensional extension of histogram threshold, both of which cannot satisfactorily handle the image segmentation for high resolution remote sensing. At present, there are many strategies combining these two methods together, such as 3-d histogram growth method, scale spatial clustering method, the dynamic clustering algorithm, etc. To some extent, they can all overcome the phenomenon of over-segmentation using a simple process of classification. However, in order to achieve more satisfactory segmentation results, some open problems are to be studied further in future, for example, problems referring to how to choose the number of clusters, how to select proper image features, how to make good use of spatial information, etc.

3 Kernel clustering

Being one important method of unsupervised learning, clustering aims at dividing the data set into several classes (or clusters), keeping the maximum similarity between the data of the same class, and the maximum difference between the data of each pair of different class [20]. At present, the research on clustering algorithm is deepening, and the kernel clustering and spectral clustering are two methods that have attracted much attention recently [21].

The main idea of kernel clustering method is to adopt a nonlinear mapping φ so that the data points in input space can be mapped into a high-dimensional feature space, to select an appropriate mercer kernel function instead of nonlinear mapping of the inner product to cluster in the feature space. The kernel clustering method is universal, and has a great advantage over the classical clustering methods. The adopted nonlinear mapping can increase the linear separable probability on input data points, which can achieve more accurate clustering, and faster convergence speed, as well. On condition that the classical clustering algorithms fail, the kernel clustering algorithms can always work. The kernel trick idea in kernel clustering method can be illustrated in Fig. 1 below, where the left is the original input space, and the right is the kernel-induced space.

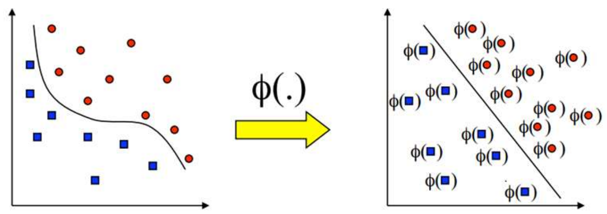


Figure 1. Nonlinearly separable problems are linearly separable in kernel-induced space

Support Vector Clustering (SVC) belongs to the method of kernel clustering, whose foundational tool for clustering is Support Vector Machine (SVM) [22]. To describe outlier detection problem more effectively with SVM, Tax and Duin (1999) proposed the Support Vector Domain Description (SVDD) algorithm [23], whose idea can be presented in Fig. 2 below. The left figure represents the decisive curve of banana-shaped data without outliers under the parameter C =1 in 2-D plane. The solid points represent the support vectors, the dotted line represents the boundary of the data description, and the grey value represents the distance from the center of sphere, where the deeper means the closer to the center. Introducing a new outlier in the right picture (located with an arrow), large change occurred in the decisive curve, where the new outlier comes into the support vector of the new decisive curve.

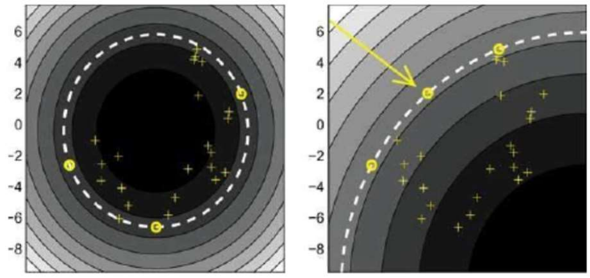


Figure 2. SVDD without outliers (left) and SVDD with outliers (right)

Based on the SVDD's idea, Ben-Hur (2001) proposed an unsupervised nonparametric clustering algorithm SVC [24], whose clustering effect on the specific value of soft margin constant C is shown in Fig. 3 beneath.

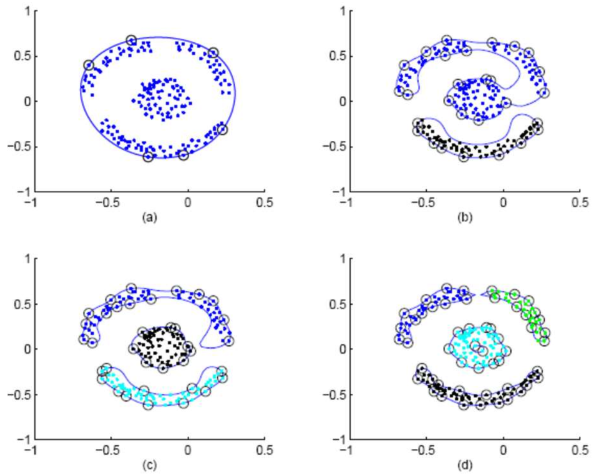


Figure 3. The clustering procedure of SVC on 183 points with C=1

SVC algorithm has two significant advantages. The first is that SVC can handle clusters with the boundary in arbitrary shape, and the second one can analyze the noise data points and separate the overlapping clusters, under circumstances when many other clustering algorithms are hard to tackle. However, SVC still has weak scalability with the number of training sample data size.

4 High resolution image segmentation

High resolution images contain relative poorer spectral information, which results in different objects with the same spectrum and the same object with various spectra, making the segmentation more difficult, or even making traditional methods fail. To make full use of spatial information contained in high resolution images, we combine the spectral features with textural and geometric features. Therefore, we proposed a novel kernel clustering algorithm to segment high resolution remote sensing images.

4.1 Statistical characteristics of texture feature

Being one essential characteristic of the image, texture can be used to fully express the surface information of the object in detail. There are many statistical methods derived from texture features, among which the ones based on gray level co-occurrence matrix (GLCM) is superior to others [25]. The common statistical characteristics used to describe gray level co-occurrence matrix include entropy, contrast, angular second moment, correlation and uniformity [26], among which we choose the first three characteristics to describe GLCM.

1) Entropy

Entropy is a statistical variable with randomness, which can describe the average information contained in images and show the heterogeneity and complexity of image texture. Entropy can be mathematically formulated as follows:

$$ENT = \sum_{i=1}^{m}\sum_{j=1}^{n} p(i,j)\log p(i,j). \tag{1}$$

where $m \times n$ is the size of image pixel, *p(i, j)* refers to the probability of pixel pair appear in image (the notions after are the same as formulated here).

2) Contrast

The contrast reflects gray level difference between images; So, the greater the contrast is, the clearer the images are. The contrast can be mathematically formulated as follows:

$$CON = \sum_{i=1}^{m}\sum_{j=1}^{n} (i-j)^2 p(i,j) \tag{2}$$

3) Angular second moment

Angular second moment represents the uniformity of image grayscale distribution, which can be mathematically formulated as follows.

$$ENE = \sum_{i=1}^{m}\sum_{j=1}^{n} p^2(i,j). \tag{3}$$

4.2 Statistical characteristics of geometry feature

Geometry feature refers to the macro-reflection of ground objects, which cannot be perceived by human's vision on the surface of the earth.

1) Average length of line

The average length of line can reflect the shape and size of ground objects in images, which can be mathematically formulated as follows:

$$LEN_{MEAN} = \sum_{i=1}^{M}\sqrt{(x_{ie}-x_{is})^2+(y_{ie}-y_{is})^2} \,/\, N \tag{4}$$

where M denotes the number of detected lines, (x_{is}, y_{is}), (x_{ie}, y_{ie}) are the coordinates of starting and ending points in the i^{th} line.

2) Entropy of line segment's length

The entropy of line segment's length can reflect the difference between different ground areas, which can be mathematically formulated as follows:

$$LEN_{ENTROPY} = \sum_{i=1}^{N} N_{LEN}(i)\log(N_{LEN}(i)) \tag{5}$$

where $N_{LEN}(i)$ is the number of line segments lying in the i^{th} interval of the length distribution histogram.

3) Average amplitude of gradient

The average amplitude of gradient can reflect the marginal information contained in images, which can be mathematically formulated as follows:

$$GRAD_{MEAN} = \sum_{i=1}^{m}\sum_{j=1}^{n}\sqrt{G_x^2(i,j)+G_y^2(i,j)} \,/\, mn \tag{6}$$

where $G_x(i,j)$ and $G_y(i,j)$ are the horizontal and vertical gradients of pixel *(i, j)*, respectively.

4.3 Statistical characteristics of spectrum feature

The spectrum is another essential feature of the ground object, and every object has its own regularity of electromagnetic radiation [27]. A remote sensing image has many spectral bands, characterized by the following three statistical features.

1) Average of pixel value

The average value reflects the mean of image, which can be mathematically formulated as follows:

$$PIX_{MEAN} = E(X) = \sum_{i=1}^{m}\sum_{j=1}^{n} X_{ij} / mn \qquad (7)$$

where X_{ij} refers to the value of pixel *(i, j)*.

2) Standard deviation of pixel value

The standard deviation reflects the connection relationship of the first-order statistics between each channel and the others, which can be mathematically formulated as follows:

$$PIX_{STD} = \sqrt{\frac{1}{nm-1}\sum_{i=1}^{m}\sum_{j=1}^{n}(X_{ij} - E(X))} \qquad (8)$$

3) Covariance matrix of pixel value

The covariance matrix reflects the connection relationship between multiple channels, which can be mathematically formulated as follows:

$$PIX_{COV} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(X_{ij} - E(X))(X_{ij} - E(X))^T}{nm} \qquad (9)$$

4.4 Process of segmentation algorithm

The detailed process of the segmentation algorithm is presented above in Fig. 4.

The SVDD method can be formulated as follows. Given a training data sets $S = \{(x_i, y_i) \mid i = 1,...,m\}$, where $x_i \in R^d$ and $y_i \in \{+1,-1\}$, the primal for the Binary SVM problem can be formulated as

$$\begin{aligned} &\min_{w,\rho,b,\xi_i} \|w\|^2 + b^2 - 2\rho + C\sum_{i=1}^{m}\xi_i^2 \\ &s.t. \quad y_i(w'\varphi(x_i) + b) \ge \rho - \xi_i, i = 1,...,m. \end{aligned} \qquad (10)$$

The corresponding dual is

$$\begin{aligned} &\min_{\alpha_i} \sum_{i,j=1}^{m} \alpha_i\alpha_j (y_i y_j k(x_i, x_j) + y_i y_j + \frac{\delta_{ij}}{C}) \\ &s.t. \quad \sum_{i=1}^{m}\alpha_i = 1,\ \alpha_i \ge 0,\ i = 1,...,m, \end{aligned} \qquad (11)$$

Denoting (x_i, y_i) as z_i, and introducing a modified map $\tilde{\phi}(z_i) = [y_i\phi'(x_i)\ \ y_i\ e'_i/\sqrt{C}]'$ with the associated kernel $\tilde{k}(z_i, z_j) = y_i y_j k(x_i, x_j) + y_i y_j + \delta_{ij}/C$, then the dual of Binary SVM with form (11) can be rewritten as

$$\begin{aligned} &\min_{\alpha_i} \sum_{i,j=1}^{m} \alpha_i\alpha_j \tilde{k}(z_i, z_j) \\ &s.t. \quad \sum_{i=1}^{m}\alpha_i = 1,\ \alpha_i \ge 0,\ i = 1,...,m. \end{aligned} \qquad (12)$$

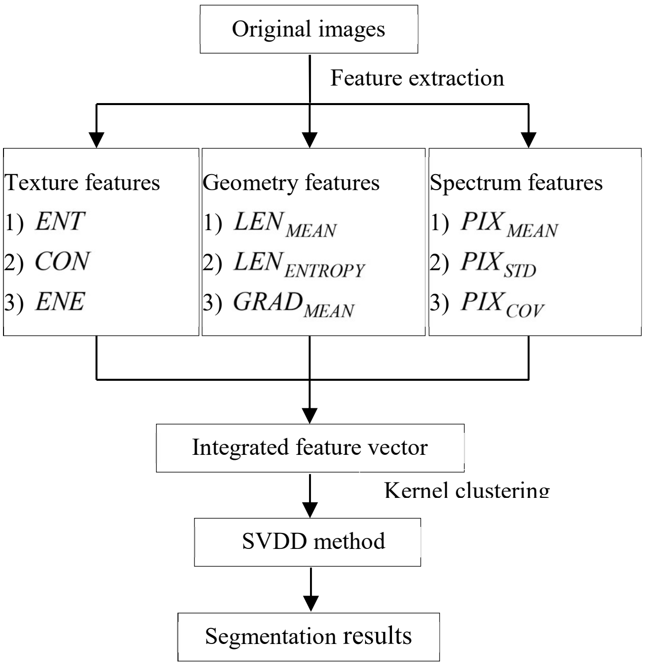
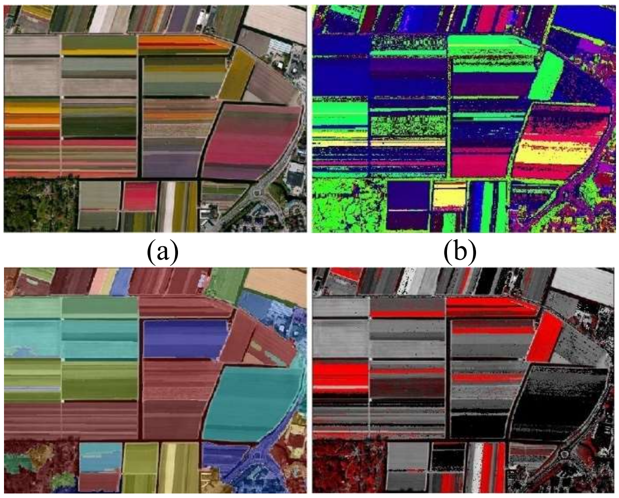


Figure 4. The flowchart of segmentation algorithm

5 Experimental results

Experiments are performed on some high resolution remote sensing images, the scenes of which are the tulip growing areas in Lisse of Dutch, salt pan in San Francisco of USA, mountain plate in Iraq, and the sizes of which are 1200×900 pixels, respectively. We use Matlab 7.0 on a PC with Pentium-4 3.20 GHz CPU, 1 GB of RAM running Windows XP to implement our experiments.

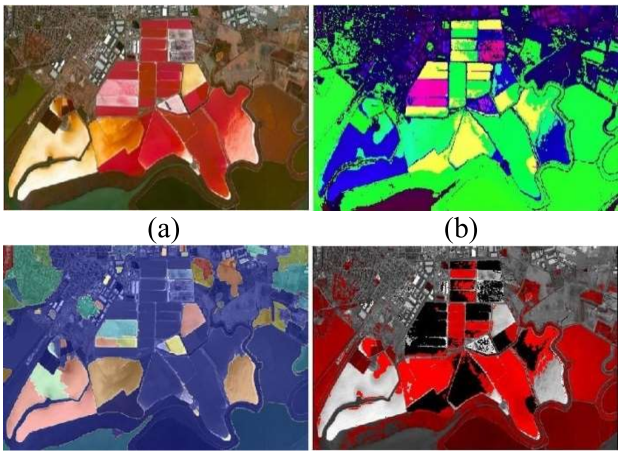
The segmentation results were conducted using the algorithms of Mean Shift (MS), Water Shed (WS), and our proposed Multi-Features Fusion (MFF) segmentation. Different performances of the three algorithms were compared in Fig. 5, 6 and 7 below.



(a) (b)

(c) (d)

Figure 5. The comparison result for tulip growing areas (original image (a) vs. segmented image by MS (b) vs. segmented image by WS (c) vs. segmented image by MFF (d))



(a) (b)

(c) (d)

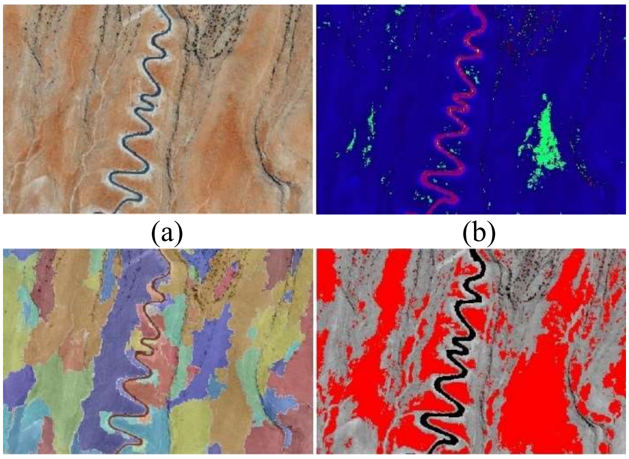
Figure 6. The comparison result for salt pan (original image (a) vs. segmented image by MS (b) vs. segmented image by WS (c) vs. segmented image by MFF (d))

From the experimental results we can see that the segmented images are comparative, except for the details list as follows.

1) Compared to the segmented images with an MS algorithm, the ones segmented with our MFF algorithm contain more spatial information so that their color features are closer to the original images.

2) Compared to the segmented images with aWS algorithm, the over-segmentation is less demanding in the images segmented with our MFF algorithm.

As a result, we can draw the conclusion that the MFF algorithm is a valid and effective method proposed for segmenting high resolution remote sensing image.



(a) (b)

(c) (d)

Figure 7. The comparison result for mountain plate (original image (a) vs. segmented image by MS (b) vs. segmented image by WS (c) vs. segmented image by MFF (d))

6 Conclusion

High resolution images contain relative poorer spectral information, which results in the facts of different objects with the same spectrum and the same object with the different spectra, and make the segmentation either be more difficult, or make it even fail providing the traditional methods were used. To make full use of spatial information contained in high resolution images, this paper combines the spectral features with textural and geometric features, by proposing a novel kernel clustering algorithm for segmenting high resolution remote sensing images. The experimental results were compared with algorithms of mean shift and watershed, which validated the effectiveness and reliability of the proposed algorithm.

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