AN EFFICIENT MULTI-SCALE SEGMENTATION FOR HIGH-RESOLUTION REMOTE SENSING IMAGERY BASED ON STATISTICAL REGION MERGING AND MINIMUM HETEROGENEITY RULE

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ABSTRACT:

Multi-scale segmentation is an essential step toward higher level image processing in remote sensing. This paper presents a new multi-scale segmentation method based on Statistical Region Merging (SRM) for initial segmentation and Minimum Heterogeneity Rule (MHR) for merging objects where high resolution (HR) QuickBird imageries are used. It synthesized the advantages of SRM and MHR. The SRM segmentation method not only considers spectral, shape, scale information, but also has the ability to cope with significant noise corruption, handle occlusions. The MHR used for merging objects takes advantages of its spectral, shape, scale information, and the local, global information. Compared with Fractal Net Evolution Approach (FNEA) eCognition adopted and SRM methods, the results showed that the proposed method overcame the disadvantages of them and was an effective multi-scale segmentation method for HR imagery.

1. INTRODUCTION

Image segmentation is the process of dividing an image into homogenous regions, which is an essential step toward higher level image processing such as image analysis, pattern recognition and automatic image interpretation (Blaschke and Strobl, 2001). So far, there are over 1000 kinds of segmentation approaches developed (Zhang, 2001). General segmentation methods include global behaviour-based and local behaviour-based methods (Kartikeyan, *et al*., 1998). Global behaviour-based methods group the pixels based on the analysis of the data in the feature space. Typical examples are clustering and histogram threshold. Local behaviour-based methods analyze the variation of spectral features in a small neighbourhood. Typical examples are edge detection and region extraction (Fu and Mui, 1981).

However, not all of the segmentation techniques are feasible for High-Resolution (HR) imagery due to the following facts:

(1) The HR imagery is multi-spectral and multi-scale, so both the complexity and redundancy are increased obviously;
(2) The HR imagery provides the more details such as spectral, shape, context and texture. The traditional segmentation algorithm is only based on the colour information and can not provide the satisfying results;
(3) Different class has its inherent feature in different scale. For example, at coarse scales we may find fields, while at finer scales we may find individual trees or plants. So the segmentation model on one scale needs to be modified when used on the other scale.

Therefore, owing to the HR imagery is multi-spectral and multi-scale, and includes more details and information of the object, it is important to segment imagery effectively with all kinds of information and object character. Recently, several authors have proposed multi-scale segmentation algorithms for HR imagery (Chen, 2003; Cheng, 2005; Sramek, 1997). A majority of image segmentation algorithms are based on region growing methods which take some pixels as seeds and grow the regions around them based on certain homogeneity criteria. The commercial software, eCognition, adopts Fractal Net Evolution Approach (FNEA) for segmentation. FNEA is a region growing technique based on local criteria and starts with one pixel image objects. Image objects are pairwise merged one by one to form bigger objects. The merging criterion is that average heterogeneity of image objects weighted by their size in pixels should be minimized (Baatz and Schape, 2000; Benz, *et al.*, 2004).

However, the local region growing technique has some limitations:

(1) It is not efficient in both computation and memory;
(2) It has some difficulties in gathering a set of seeds and an adequate homogeneity criterion;
(3) It depends on the choice of starting point and the order in which the pixels and regions are examined;
(4) It is hard to find coincident boundary because one pixel image object merges with another without respect of adjacent pixels.

In order to overcome the disadvantages of segmentation from one pixel and get more accurate segmentation result, several authors suggest merging bigger objects generated by initial segmentation, which avoids of the disadvantages of region growing method from single pixel.

In this paper, a multi-scale segmentation method based on Statistical Region Merging (SRM) and Minimum Heterogeneity Rule (MHR) is presented. The choice of SRM depends on both the ability to cope with significant noise corruption, handle occlusions and the consideration of spectral, shape, scale information. The application of MHR relies on both the effectiveness local quality and global quality and its consideration of shape and spectral features. We take the advantages of them by applying SRM for initial fine segmentation and MHR for region merging.

2. MULTI-SCALE SEGMENTATION BASED ON SRM AND MHR

2.1 Statistical Region Merging

The SRM algorithm belongs to the family of region growing techniques with statistical test for region fusion, and it is based on a model of image generation who captures the idea that grouping is an inference problem, namely, the observation imagery comes from the original imagery by sampling, and the segmentation imagery comes from the observation imagery by regenerating, the homogeneity region boundary may defined by simple theorem (Nielsen and Nock,2003; Nock and Nielsen, 2004).The two key steps of the algorithm are as follows:

(1) Ascertain a sort function, by which the adjacent regions are sorted according to the size of the function;
(2) Ascertain a merging predicate, which confirms whether the adjacent regions are merged or not. It is obvious that sort function and merging predicate are basis of the algorithm and they are interactive with each other.

Supposing I is an image with $|I|$ pixels each containing three values (R,G,B) belonging to the set $\{1,2,...,g\}$. The observed imagery I' is generated by sampling, in particular, every colour level of each pixel of I' is described by a set of Q independent random variables with values in $[0, g/Q]$. In I' the optimal regions satisfy the following homogeneity properties:

(1) A homogeneity property: inside any statistical region and for any channel, statistical pixels have the same expectation value for each channel;
(2) A separability property: the expectation value of adjacent regions is different for at least one channel (Nock, 2001).

Nielsen and Nock consider a sort function f defined as follows:

$$f(p,p') = \max_{a\in\{R,G,B\}} |p_a^{'} - p_a| \tag{1}$$

Where, $p_a^{'}$, p_a stand for pixel values of a pair of adjacent pixels of the channel a. From the Nielsen and Nock model obtains the following merging predicate:

$$P(R,R') = \begin{cases} true. & if\ \forall a \in \{R,G,B\}, |\overline{R}_a^{'} - \overline{R}_a| \le \sqrt{b^2(R)+b^2(R')} \\ false. & otherwise \end{cases} \tag{2}$$

Where, $b(R) = g\sqrt{\frac{1}{2Q|R|}(\ln\frac{|R_{|R|}|}{\delta})}$, $\overline{R}_a$ denotes the observed average for channel a in region R, $R_{|R|}$ stands for the set of regions with R pixels. More sort functions and merging predicates could be used to define, which could improve the speed and quality of segmentation.

In conclusion, the SRM algorithm is able to capture the main structural components of imagery using a simple but effective statistical analysis, and it has the ability to cope with significant noise corruption, handle occlusions with the sort function, and perform multi-scale segmentation(Nielsen and Nock,2003; Nock and Nielsen, 2004; Nock and Nielsen, 2005). However, it has the disadvantage of over-merging, and is not applied in remote sensing imagery. In this paper, we optimize and apply it in HR imagery for initial fine segmentation.

2.2 Minimum Heterogeneity Rule

In order to implement the multi-scale segmentation, the MHR is introduced to merge two adjacent regions from the initial segmentation.

A MHR not only considering the colour heterogeneity (h_{color}) but also shape heterogeneity (h_{shape}) is defined as follows:

$$h = w_{color}h_{color} + w_{shape}h_{shape} \tag{3}$$

Where, w_{color} , w_{shape} are weight values about colour heterogeneity and shape heterogeneity respectively, and $w_{color} \in [0,1]$, $w_{shape} \in [0,1]$, $w_{color} + w_{shape} = 1$.

The colour heterogeneity h_{color} is defined as follows:

$$h_{color} = \sum_c w_c(n_{merge}\cdot\sigma_{c,merge} - (n_{obj\_1}\cdot\sigma_{c,obj\_1} + n_{obj\_2}\cdot\sigma_{c,obj\_2})) \tag{4}$$

Where, w_c indicates weight value of every channel. σ_{c,obj_1}, σ_{c,obj_2}, $\sigma_{c,merge}$ are the deviation of the two region and the merged region respectively. n_{obj_1}, n_{obj_2}, n_{merge} are the numbers of the two adjacent regions and the merged region. This value indicates the similar degree of the two adjacent regions.

The shape heterogeneity (h_{shape}) describes the changes of compact degree (h_{compt}) and smooth degree (h_{smooth}) before and after two adjacent regions are merged. h_{shape} , h_{compt} , h_{smooth} are defined as follows:

$$h_{shape} = w_{compt}h_{compt} + w_{smooth}h_{smooth} \tag{5}$$

$$h_{compt} = n_{merge}\cdot\frac{l_{merge}}{\sqrt{n_{merge}}} - (n_{obj\_1}\cdot\frac{l_{obj\_1}}{\sqrt{n_{obj\_1}}} + n_{obj\_2}\cdot\frac{l_{obj\_2}}{\sqrt{n_{obj\_2}}})$$

$$h_{smooth} = n_{merge}\cdot\frac{l_{merge}}{b_{merge}} - (n_{obj\_1}\cdot\frac{l_{obj\_1}}{\sqrt{b_{obj\_1}}} + n_{obj\_2}\cdot\frac{l_{obj\_2}}{\sqrt{b_{obj\_2}}})$$

Where, w_{compt} , w_{smooth} are weight values about compact heterogeneity and smooth heterogeneity respectively. And $w_{compt} \in [0,1]$, $w_{smooth} \in [0,1]$, $w_{compt} + w_{smooth} = 1$.

n_{obj_1}, n_{obj_2}, n_{merge} are the numbers of the two adjacent regions and the merged region respectively. l_{obj_1}, l_{obj_2}, l_{merge} are the boundary length of the adjacent regions and the merged region respectively. b_{obj_1} , b_{obj_2} , b_{merge} are the perimeter of the bounding box of the two adjacent regions and the merged region respectively.

The value of h_{compt} represents the cluster degree of the pixels in the region. Smaller the value is, more compact the pixels in the region. The value of h_{smooth} represents the smoothness degree of the region boundary. Smaller the value is, Smoother the region boundary is.

In a word, the MHR not only considers colour information, but also shape information which could reduce the disturbance of noise, and debase fragmentized degree of object boundary, and get more regular objects.

2.3 Multi-scale Segmentation based on SRM and MHR

On the basis of analysing the SRM and MHR algorithm, a new multi-scale segmentation algorithm is presented, where the SRM is improved and applied in HR imagery for getting initial fine segmentation results, and the MHR is used for merging two adjacent regions from the initial segmentation results.

The improvements of the SRM algorithm itself are as follows:

(1) Make full use of all bands information of remote sensing imagery. The original algorithm is only suitable for grey and colour image, we improved and applied it in remote sensing imagery with many bands.

(2) Define scale parameter S and set up the relationship between S and the independent random variables Q. Since the SRM has the ability of multi-scale segmentation, S is defined to satisfy the direct relationship between the imagery scale and the object size. Namely, the bigger the scale is, the bigger the object size is, the more the object numbers are.

(3)Define merging predicate more strictly. Since $\sqrt{b^2(R)+b^2(R')} \le b(R)+b(R')$, the strict merging predicate is therefore:

$$P(R,R') = \begin{cases} true. & if \quad \forall a \in \{B1, B2, ..., Bn\}, |\overline{R}'_a - \overline{R}_a| \le b(R)+b(R') \\ false. & otherwise \end{cases} \quad (6)$$

Where, $b(R) = g\sqrt{\frac{10000}{2S|R|}(\ln\frac{|R_{|R|}|}{\delta})}$, S is scale parameter, $\overline{R}_a$ denotes the observed average for channel a in region R, $R_{|R|}$ stands for the set of regions with R pixels. $B1, B2, ..., Bn$ are channels of imagery.

Therefore, the flowchart of the multi-scale segmentation algorithm based on SRM and MHR is shown in figure 1 which comprises two main progresses: the initial segmentation progress by the improved SRM algorithm, and the merging progress by the MHR algorithm.

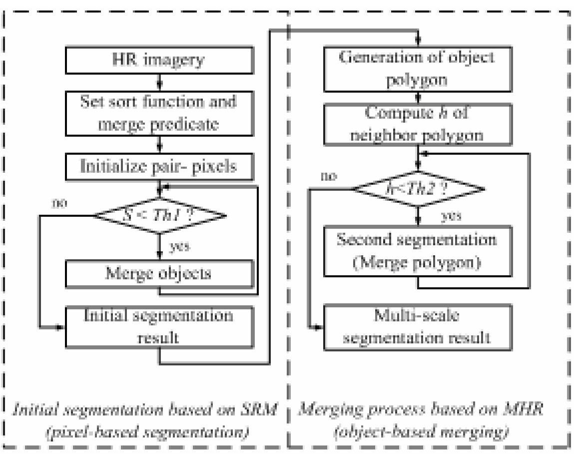

Figure 1. The flowchart of the Multi-scale segmentation based on SRM and MHR.

There are four steps in the initial segmentation progress:

(1) Set the sort function shown in formula (1), and then sort the pair-pixels according to the size of the function.

(2) Ascertain the merge predicate shown in formula (2) which is relative with pair-pixels, and make sure the position of up level nodes the pairs belong to.

(3) Judge whether the seeds of pair-pixels are at the same position, and whether they satisfy the merge predicate. If their positions are not identical and they satisfy the merge predicate($S<Th1$), then the pair-pixels are merged, meanwhile, the area is updated with the sum of the pair-pixels.

(4) Repeat step 2-3 until all the pair-pixels are segmented by the approach. Then an initial segmentation result which is based on pixel-based segmentation is realized.

As to the multi-scale segmentation, there are four steps in the merging progress:

(1) Object polygons are generated by vectorization algorithm. The key steps are the search of boundary, the generation of topology structure, and the remove of redundant points. Then the information such as topology structure, pixel numbers, mean, deviation and boundary length are stored in a vector file and an attribute file.

(2) Set the parameters of MHR, such as w_{color}, w_{shape}, w_{compt}, w_{smooth}, $Th2$. And then compute heterogeneity value h of neighbour polygon according to formula (3).

(3) Judge whether h satisfy MHR, if $h<Th2$, the adjacent smaller objects are merged into other bigger ones, meanwhile, the average size, deviation and mean of all the object regions will be calculated.

(4) Repeat step 2-3 to accomplish multi-scale segmentation.

This relationship between each level is shown in figure 2.

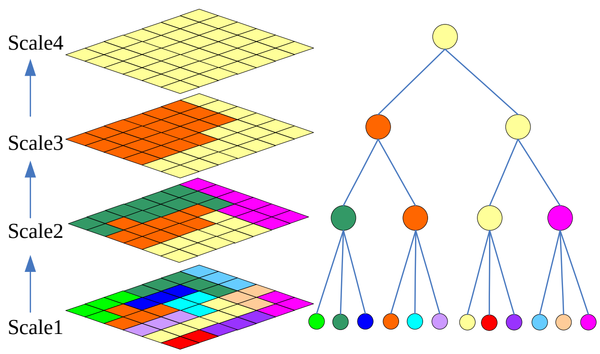

Figure 2. Four-scale hierarchical network of image objects

Scale1 stands for initial segmentation level based on pixel-based segmentation, scale2, scale3 and scale4 stand for multi-scale segmentation level based on object-based merging. To guarantee a definite hierarchy over the spatial shape of all objects the segmentation procedures follow the following rules (Benz, 2004):

(1) Object borders must follow borders of objects on the lower scale.

(2) Segmentation is constrained by the border of the object on the upper level.

(3) The correction of object shape based on merging sub-objects is possible.

3. SEGMENTATION EXPERIMENT

3.1 Experiment data

To evaluate the performance of the proposed segmentation approach, a multi-spectral QuickBird imagery at 2.44-m resolution and a panchromatic QuickBird imagery at 0.61-m resolution, which were acquired in May 2005 in HeFei city of China were used. The area is about 1023 × 822 pixels and represents a complex urban environment. The selected part of the city is characterized by classes of road, highway, grass, and building. Initially, the QuickBrid imagery were geometrically corrected to the universal transverse Mercator (UTM) projection, and re-sampled to 0.61-m to match the image pixel size, and then fused by the Smoothing Filter-based Intensity Modulation(SFIM) method using the CASM ImageInfo® remote sensing imagery processing software (CASM Imageinfo, 2007) developed by Chinese Academy of Surveying and Mapping. The SFIM is a superior fusion technique for improving spatial detail of multispectral images with their spectral properties reliably preserved (Liu, 2000), and fusion strategy is helpful for improving classification accuracy (Xu, 2004; Cao,2006). Figure 3(a) shows the panchromatic QuickBird image, and figure 3(b) shows the multi-spectral QuickBird composite image of band 4(infra-red), band 2(green), and band 1(blue). Figure 3(c) shows the fused image compositing from the same bands as figure 3(b).

3.2 Segmentation Experiment

Initially, we segmented the fusion image by the improved SRM segmentation algorithm to get the initial segmentation result on the basis of the SRM software package. The key issue is trying to adjust parameter until getting better initial segmentation result, then these segmented imagery was vectorized in coverage format using ERDAS imagine 8.7® (ERDAS imagine, 2003). Figure 3(d) shows the vector image overlaid on the initial segmentation result.

Then, the objects from the initial segmentation were merged by the MHR method, meanwhile the objects information such as mean, boundary length, deviation is recomputed for latter merging operation. Figure 3(e) and figure 3(f) show the course scale imageries when the scale threshold is 40 and 60 respectively. Table 1 shows the detail parameters.

Segmentation level	Scale	Color	Shape		Object numbers
			w_{smooth}	w_{compt}	
Level 1	8	0	0	0	702
Level 2	40	0.6	0.3	0.7	374
Level 3	60	0.5	0.2	0.8	185

Table 1. The parameters of the new method

In order to evaluate the performance of the proposed method, we also segmented the fused QuickBird imagery using FNEA that the eCognition soft adopted. The multi-scale segmentation results are shown in figure 3(g), figure 3(h), figure 3(i), and detail parameters are shown in table 2. Moreover, we carried on multi-scale SRM segmentation, and the results are shown in figure 3(j), figure 3 (k), figure 3 (l), and detail parameters are shown in table 3.

Segmentation level	Scale	Color	Shape		Object numbers
			w_{smooth}	w_{compt}	
Level 1	100	0.6	0.3	0.7	528
Level 2	150	0.6	0.3	0.7	270
Level 3	180	0.5	0.3	0.7	186

Table 2. The parameters of eCognition

Segmentation level	Scale	Object numbers
Level 1	8	702
Level 2	16	401
Level 3	22	294

Table 3. The parameters of SRM

3.3 Accuracy Assessment

As shown in figure 3(g), we notice that the FNEA method always divides the big homogeneity region into lots of small regions with the similar size, especially highway. The limitation may be resolved by merging the same classes, but it is based on initial segmentation objects. When the scale becomes bigger, there still has the phenomena shown in figure 3(f). This is caused by the assumption that the objects with same scale have similar size which is in consistent with nature phenomena. As we know, building, road, grass and woodland belong to the same level of land cover class, however, their sizes are different greatly.

We also notice that there have small redundant objects shown in figure 3(j). The redundant objects may be wiped off when the scale becomes large, but there remains the limitation all the same shown in figure 3(l).

However, the new proposed method overcomes these limitations by SRM acting as initial segmentation. As shown in figure 3(d), we notice that the highway is integrally detached avoiding of smash objects. When the scale becomes bigger, some classes such as highway, building, grass are easy to extract, and there is less small objects shown in figure 3(f). The bigger the scale is, the fewer the object numbers are, the bigger the object region is, and the boundary of region may disappear or remain.

Obviously, the new multi-scale segmentation method shows advantages over traditional multi-scale SRM and FNEA algorithm in the following aspects:

(1) It makes full use of shape, spectral, scale, local, global information and the parameters could adjust for various classes.
(2) It integrates the superiorities of SRM segmentation method and MHR merging method, and avoids the disadvantages of these methods.
(3) The segmentation result described both in vector and raster format integrates RS and GIS expediently, and establishes better foundation for higher level image processing such as pattern recognition and automatic image interpretation.

4. CONCLUSION AND DISCUSSION

This study proposed a new multi-scale segmentation method based on SRM and MHR where QuickBird imageries are used. Compared with multi-scale SRM and FNEA method, the results indicates that the proposed method overcomes the disadvantages of them, integrates the advantages of them and is an efficient multi-scale segmentation for HR imagery. The SRM method used for initial segmentation achieves robust and accurate segmentation results through using not only the spectral, shape, scale information, but also has the ability to cope with significant noise corruption, handle occlusions. The MHR used for merging objects relies on both the effectiveness local quality and global quality and its consideration of shape and spectral features.

Nevertheless, there are many other issues that require future investigation, including the improvement of sort function and merge predicate of SRM, the study of evaluation index for estimating segmentation results, the determination of parameters for various classes, and the applications of the proposed method in different styles of RS imagery such as SAR, and so on.

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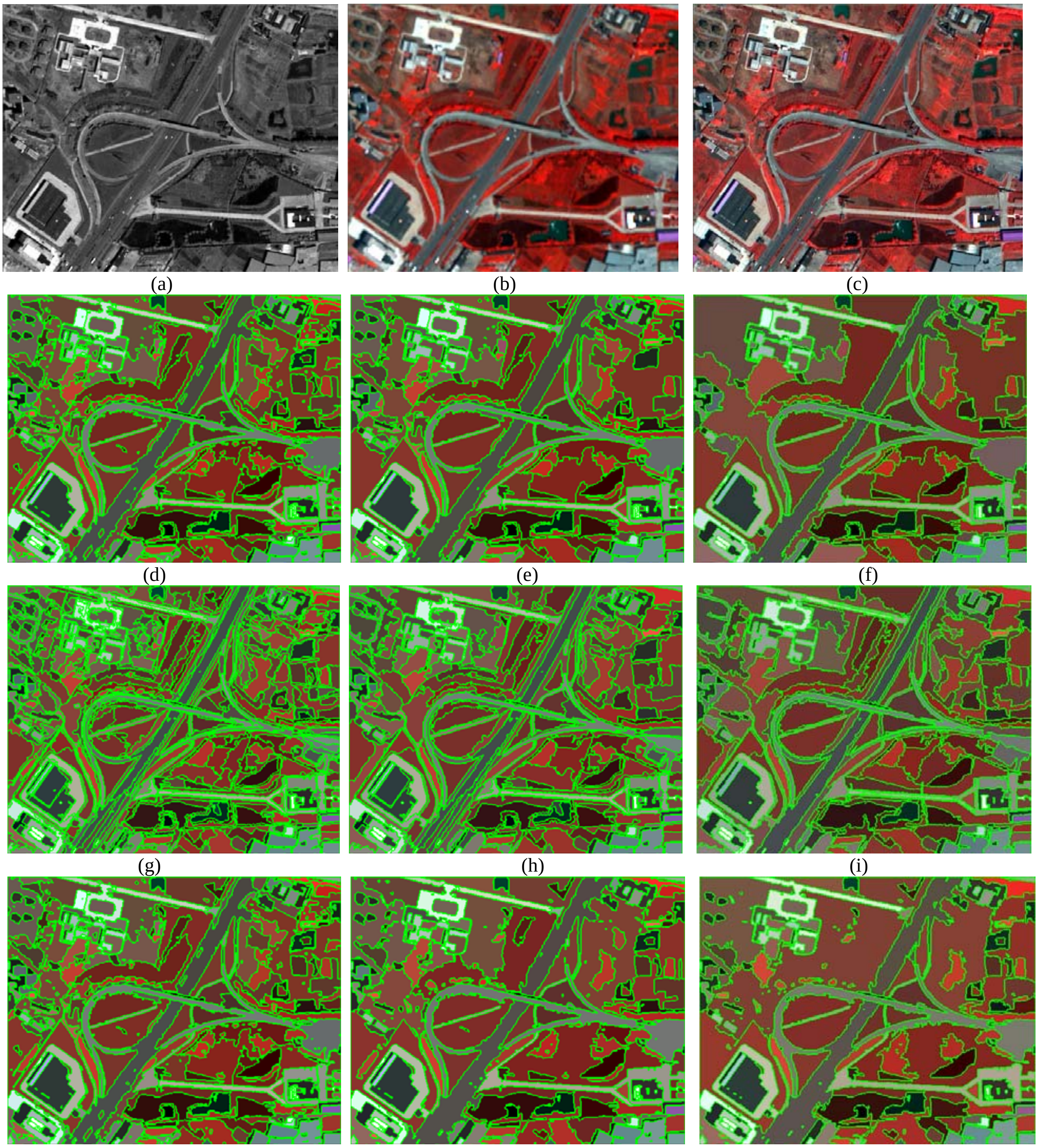

(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k) (l)

Figure 3. (a) Panchromatic image. (b)Multi-spectral image. (c) The SFIM fused image. (d) Initial segmentation result of SRM using scale parameter 8. (e) The new method's result with scale parameter 40. (f) The new method's result with scale parameter 60. (g) eCognition's result with scale parameter 100. (h) eCognition's result with scale parameter 150. (i) eCognition's result with scale parameter 20. (j) SRM's result with scale parameter 8. (k) SRM's result with scale parameter 16. (l) SRM's result with scale parameter 22.