SELECTING OPTIMAL SLIC SUPERPIXELS PARAMETERS BY USING DISCREPANCY MEASURES

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ABSTRACT

Segmentation is the first and most crucial step of object-based image analysis in that an image is partitioned into homogenous areas, known as superpixels, considering the spectral, textural and contextual information of contiguous pixels. Superpixels have become popular for use particularly in computer vision. By considering superpixels instead of pixels redundancy and complexity in processing stage are minimized. In this study, Simple Linear Iterative Clustering (SLIC) superpixel segmentation method was evaluated for the generation of image objects by varying parameter values to search the optimal values. Based on the discrepancy between reference polygons and corresponding image segments, the ideal combination of SLIC parameter values were determined. To evaluate the segmentation quality of SLIC superpixels, five discrepancy metrics, namely under-segmentation, over-segmentation, potential segmentation error (PSE), number-of-segments ratio (NSR) and Euclidean distance 2 (ED2) were applied by considering manually digitized reference polygons. A Worldview-2 and a Quickbird-2 image covering two test sites from Turkey were employed, and four superpixel sizes (5x5, 10x10, 15x15 and 20x20) were evaluated to test the image objects quality. Results showed that the proposed metrics used to identify optimal combinations of parameters revealed the optimal size of superpixels size as 10x10 pixels. It was also observed that over-segmentation and the process time can be reduced by selecting the appropriate superpixel parameters.

1. INTRODUCTION

In parallel with the latest innovations in satellite technology, the use of very high resolution (VHR) satellite imagery has become more available in remote sensing operations. Detailed geospatial information and precise digital information data is performed in VHR images (Zhang et al., 2015). However, it is not simple to attain precise information from VHR images due to the big volume of geospatial data and complicated ground information (Chen et al., 2014). Such problems have contributed to the switch from pixel-based approach to object-based approach (Blascke et al., 2014; Blascke, 2010; Garcia-Pedrero et al., 2015). Object-based image analysis (OBIA) provides better performance in VHR image analysis because it deals with not only the spectral information but also the spatial, textural and contextual information when compared to pixel-based approach (Corcoran and Wınstanley, 2007; Kavzoglu, 2017). Segmentation is the first and most critical step of OBIA, aiming to partition an image into homogenous regions. The characteristic of the image objects is determined by some strategies and algorithms used in the segmentation process. Although there are many methods of segmentation in computer vision, most methods and algorithms have deficiencies (Garcia-Pedrero et al., 2015). Therefore, selection of the ideal segmentation method with optimum parameters is a prerequisite for the subsequent classification or feature extraction applications (Kavzoglu et al., 2016).

In recent years, the use of superpixel methods has evolved considerably in the area of remote sensing (Csillik, 2017). Garcia-Pedrero et al. (2015) generated superpixels and edge-based processing to automatically obtain well-defined agricultural parcels. Csillik (2017) used SLIC superpixels on VHR satellite images to compare with traditional pixel-based and object-based approaches. Compared to pixel-level methods, superpixel methods can be more suitable for remote sensing applications with useful spatial information that they offer reducing redundant image information and more effective in complex image processing (Ma et al., 2016). Superpixels are homogeneous image regions that consist of spatially associated similar pixels. They produce meaningful image objects (segments) and provide less computational time for later steps including classification, clustering and segmentation stages. Among the proposed methods for superpixel evaluation, the Simple Linear Iterative Clustering (SLIC) has been reported to be more effective than the other methods by keeping the under-segmentation errors at a minimum level and standard boundary recall (Achanta et al., 2012).

Although the use of superpixel methods is actively used in the computer vision area, their uses in the remote sensing applications have not been completely explored (Garcia-Pedrero et al., 2015). To the best of our knowledge, there are only a few papers on the quality analysis of superpixel sizes in the remote sensing literature. The objective of this study can be twofold: (1) the usage of SLIC superpixels segmenting VHR satellite images and (2) comparing the effect of different SLIC superpixel sizes upon the segmentation quality using five discrepancy measures.

2. STUDY AREA AND DATASET

Two study sites with different landscape characteristics were chosen for this study. Worldview-2 and Quickbird-2 images of these sites were employed in processing stages (Figure 1). For the first test area, a pan-sharpened multispectral 8-band Worldview-2 image acquired on July 12th, 2012 was used. This particular area covers 2000x2000 pixels in Bayramoglu peninsula of Kocaeli province of Turkey and mainly consists of recreational fields, forested lands, and urban areas. For the second test area, a multispectral pan-sharpened Quickbird-2 satellite image having four spectral bands at 0.6m spatial resolution acquired on May 5th, 2008 was used. The area covers 1420x1450 pixels in Trabzon province of Turkey. It can be described as a semi-urban site, including sea with beach, a residential area, main roads, urbanization and industrialization sites. All analyses were conducted on ArcGIS software (v.10.0) with Python scripting language.

Figure 1. Location of study areas (Test area-1 and Test area-2)

3. METHODOLOGY

3.1 SLIC Superpixels

Superpixels are statistically homogeneous image regions composed of small, local and coherent clusters, which are formed according to certain criteria such as color texture etc. (Ren and Malik, 2003; Gonzalo Martín et al., 2015). Although there are many superpixel algorithms, they are mostly at a low computational speed and have some limitations (Achanta et al. 2012). The SLIC superpixel method, as a new type of image segmentation approach, was originally developed in computer vision area by Achanta et al. (2010).
The SLIC superpixel segmentation algorithm has been reported to outperform other state-of-the-art methods by producing better quality segments with low processing time and memory cost. This method produces superpixels by clustering pixels based on their color similarity and proximity in the image plane by using only one parameter, which is the desired number of equally sized superpixels to be generated (Achanta et al., 2012; Csillik and Lang, 2016). SLIC is an adapted *k*-means clustering based on the idea of limiting the search space to a region proportional to the desired superpixel size. The algorithm is specifically tailored to perform superpixel clustering using the distance measure of Eq. (1) and localizes the pixel search to an area ($2S \times 2S$) on the image plane.

$$d_{lab}=\sqrt{(l_k-l_i)^2+(a_k-{a_i}^2)+(b_k-b_i)^2} \quad (1)$$

$$d_{xy}=\sqrt{(x_k-x_i)^2+(y_k-y_i)^2)} \quad (2)$$

$$D_s=d_{lab}+\frac{m}{S}d_{xy} \quad (3)$$

where L, a and b are the CIELAB color space values, m is the compactness of superpixel, D_S is the sum of the lab distance and the xy plane distance is normalized by the grid interval S. Detailed description and working principle of SLIC algorithm can be found in Achanta et al. (2010).

3.2 Segmentation Accuracy

Segmentation is the initial and fundamental step of image analysis workflow. There are many segmentation algorithms that utilize various parameters to control characteristics of output segments (Kavzoglu et al., 2016; 2017). However, selecting optimal parameter combination is a long-term and tedious process (Kavzoglu and Yildiz, 2014). In many studies, optimum parameter values are determined by discrepancy between a reference polygon and a corresponding segment as segmentation evaluation criteria of image. In the ideal case, the expected situation is that over-segmentation and under-segmentation should be minimum level to achieve high-quality image segmentation (Neubert et al., 2008; Kavzoglu et al. 2017).

In this study, five segmentation discrepancy metrics namely under-segmentation (Clinton et al.2010), over-segmentation (Clinton et al.2010), potential segmentation error (PSE), number-of-segments ratio (NSR) and Euclidean distance 2 (ED2) were used to determine optimal SLIC superpixel parameter. Over-segmentation (OS) and under-segmentation (US) metrics estimate the 'closeness' of the image objects to the reference data (Clinton et al., 2010). In the ideal case of a perfect match between evaluated segments and reference polygons, OS and US would be zero. The PSE index, calculates the ratio between the total area of under-segments and the total area of reference polygons (Liu et al., 2012). The PSE value of zero indicates that there are no under-segments in the segmented image. On the other hand, the NSR index measures the absolute difference between the number of reference polygons and number of corresponding image objects divided by the number of reference polygons (Liu et al., 2012). This index shows the arithmetic discrepancy in the situation of over-segmentation (Liu et al., 2012). Moreover, the ED2 index is a Euclidean distance that considers both geometric and arithmetic discrepancies. A large ED2 value shows a noteworthy geometric or arithmetic discrepancy or both (Liu et al., 2012).

4. RESULTS AND DISCUSSION

In order to fulfil the objectives of this study, two VHR images (i.e. WorldView-2 and Quickbird-2) were used to determine the optimal combinations of parameter values on size of superpixels employing selected discrepancy measures. Also, four superpixel sizes (5x5, 10x10, 15x15 and 20x20) were evaluated to determine the optimal superpixel sizes of the test images (Figure 2). All tests were conducted on a personal computer with Intel Core i5-4200H CPU (2.80 GHz) processor with 12 GB RAM, using a 64-bit Windows 8.1 operating system.

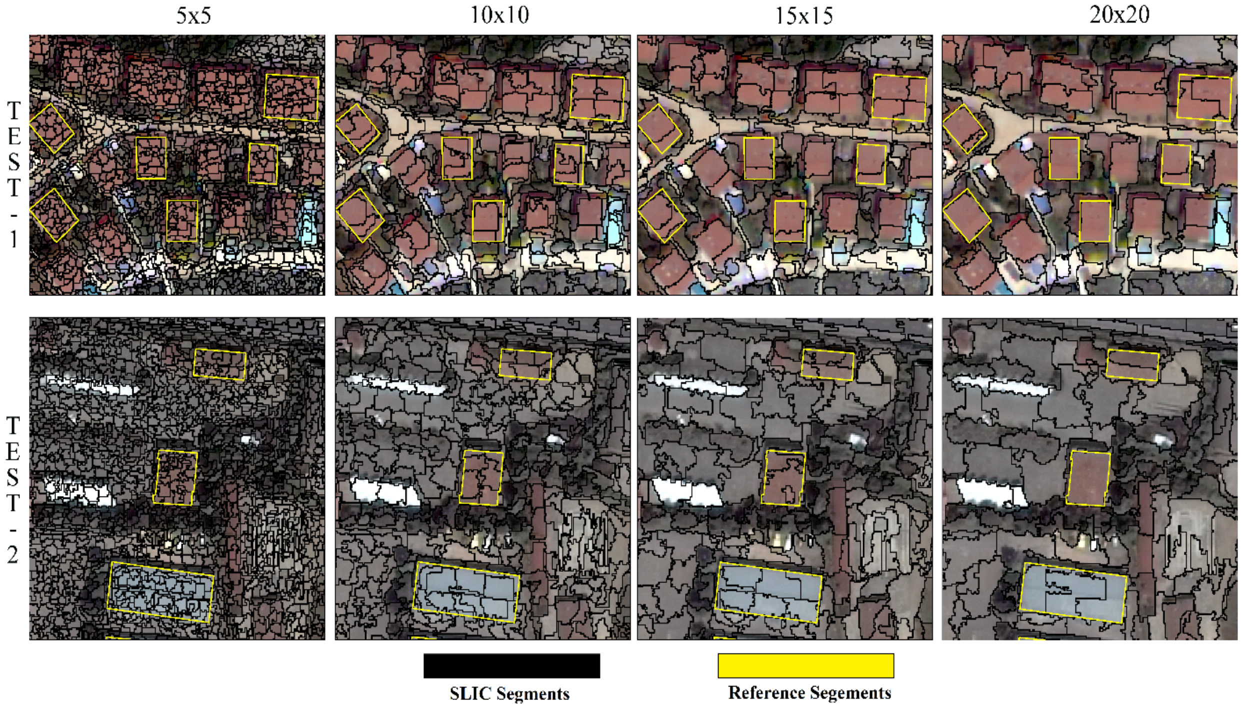


Figure 2. Subset Images of SLIC segmentation results, starting from initial size of the superpixels of 5×5, 10×10, 15×15 and 20×20.

SLIC superpixels are generated using open-source GDAL implementation, available on https://github.com/cbalint13/gdal-segment. The program implements various segmentation algorithms over raster images. It can be used to segment multispectral and hyperspectral satellite imagery. The tool requests following parameters: input raster image, output shapefile of superpixel polygons, the superpixel algorithm to be used (SLIC, SLICO, LSC, SEEDS), the number of iterations (the default is 10) and the size of the superpixels to be generated (the default is 10) (Csillik, 2017). Default value of 10 was selected for iterations, selected for clustering superpixels, as suggested by Achanta et al. (2012). As shown in Table 1, a number of image objects ranging from 3,865 to 153,689 were produced using four different superpixel sizes for both test sites. Afterwards, segmentation quality evaluation was conducted using 40 and 25 manually digitized reference buildings for test area-1 and test area-2, respectively. The five discrepancy index metrics namely, under-segmentation, over-segmentation, potential segmentation error (PSE), number-of-segments ratio (NSR) and Euclidean distance 2 (ED2) were utilized, with a minimum percent overlap of 50% as suggested by other researchers (e.g. Yang et al., 2015; Csillik, 2017). The OS and US metrics were calculated using ArcGIS software package (v.10.0). The other discrepancy measures (NSR, PSE, ED2) were computed by using a free of charge command line tool (AssesSeg), created by Novelli et al. (2017). The executable source code of tool was written in Python 2.7 using open source libraries. The SLIC segmentation accuracy results and computational times for both test sites are presented in Table 1.

Table 1. Comparison of SLIC segmentation accuracy and computational times for both test sites

	Segmentation Results		**Segmentation Accuracy**					**Time (sec)**
	SLIC Size	**No. of objects**	**OS**	**US**	**NSR**	**PSE**	**ED2**	
Test 1	5x5	153,689	0.034	0.093	26.676	0.069	26.676	276
	10x10	35,580	0.043	0.137	5.225	0.107	5.226	47
	15x15	14,951	0.064	0.184	1.675	0.163	1.683	30
	20x20	8216	0.081	0.228	0.750	0.216	0.781	23
Test 2	5x5	81,797	0.025	0.058	49.120	0.056	49.120	65
	10x10	17,299	0.036	0.105	10.240	0.095	10.240	20
	15x15	7160	0.041	0.134	4.280	0.149	4.283	13
	20x20	3865	0.047	0.164	1.960	0.196	1.969	10

Table 1 shows the segmentation goodness results achieved and the corresponding image objects numbers for the both test sites. It is worth noting that the 5x5 SLIC superpixel sizes always produced better image objects in terms of the quality metrics for both test areas. However, when the segment number and the computation time of the 10x10 superpixel size are compared to the size of the 5x5 superpixel size, it has been observed that 10x10 superpixel size provides considerable improvement but the over-segmentation does not change much and provides a good alternative. It was also observed that 20x20 SLIC superpixel sizes created inconsistent segments and produced the worst accuracy results. As an example, compared to 20x20 superpixel size, 5x5 superpixel size had better values of ED2 for the first site (26.676 as opposed to 0.781), and for the second site (49.120 as opposed to 1.969). The computational time ranged from 276 to 23 seconds for the first site and 62 to 10 seconds for the second test site. Since the first study site had a scene with a larger number of bands, it definitely required much more calculation for segmentation.

Despite the fact that 5x5 superpixel size gave the best results for segmentation in terms of goodness measures, it had some drawbacks for optimal parameter selection. The most important disadvantage was that the 5x5 superpixel sizes had an excessive computational time and the over-segmentation was high, especially when the NSR index values were taken into consideration. Liu et al. (2012) states that “although not a true error, a significant degree of over-segmentation is undesirable when attempting to obtain meaningful segments”. Considering the segmentation speed and the number of segments to be produced, it was concluded that the use of 10x10 sizes would be more suitable in parameter selection.

Furthermore, a supervised classification using the nearest neighbor classifier for optimum superpixel sizes (10x10) was performed on both images. Images were classified using spectral bands with 37 and 20 spectral features (mean, maximum, minimum, band ratio, HIS, NDVI) for test area 1 and test area 2, respectively. The classification accuracies (overall accuracy and Kappa coefficient) were estimated from confusion matrices using validation datasets that include equal number of samples (1,500 samples per class for the first scene, and 2,500 samples per class for the second scene) to avoid bias towards a certain LULC category. Performances of the optimal SLIC superpixel sizes for both images were also analyzed based on individual class accuracies (Table 2).

Table 2. Accuracy Assessment Results for both test sites

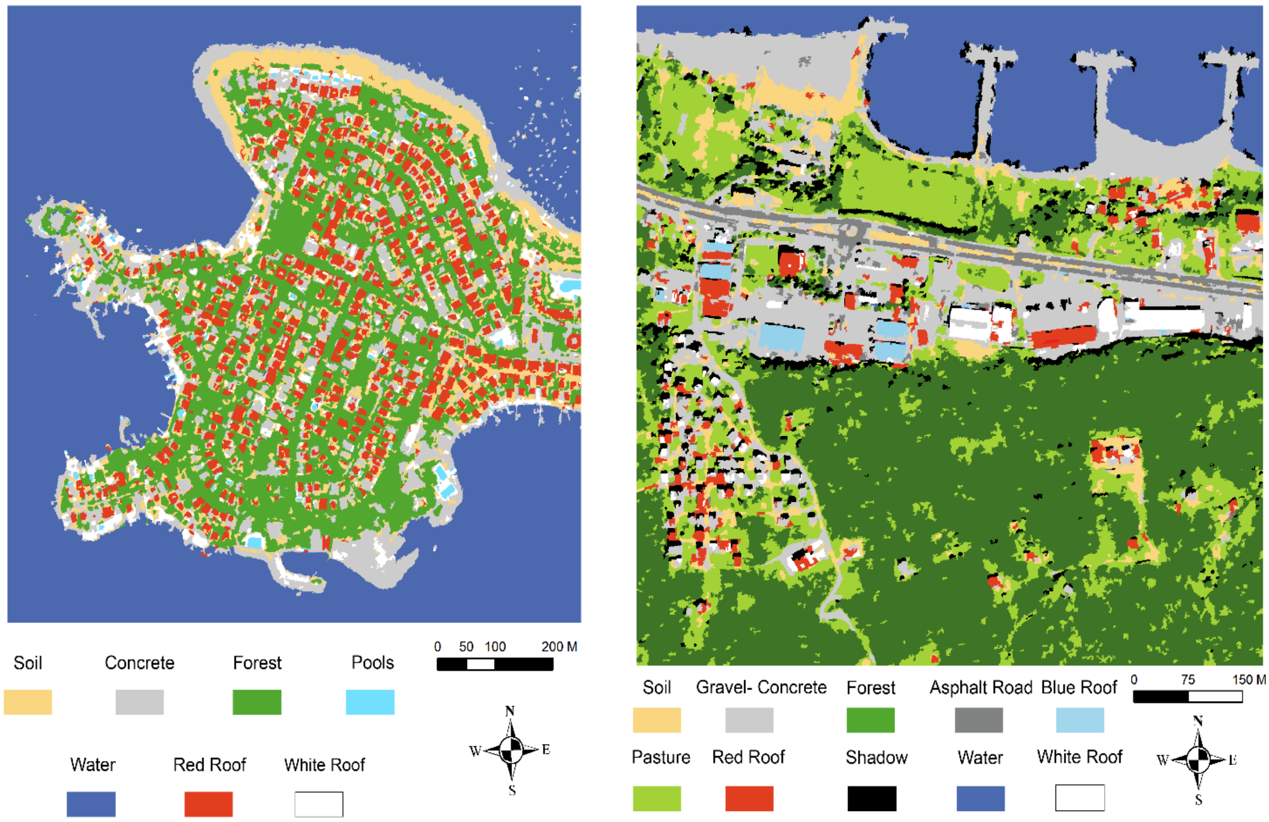
Test Area 1

Class	**Producer's**	**User's**
Concrete	76.60	88.11
Forest	91.67	95.09
Pools	99.93	100
Red Roof	98.80	96.86
Soil	95.13	88.63
Water	86.73	71.76
White Roof	84.07	97.15
Overall Acc.	90.42%	
Kappa	0.89	

Test Area 2

Class	**Producer's**	**User's**
Asphalt Road	69.52	81.18
Soil	95.88	77.10
Blue Roof	95.16	80.05
Forest	86.72	96.61
Gravel-Concrete	92.32	99.83
Pasture	79.52	92.34
Red Roof	85.48	74.25
Shadow	92.44	98.01
Water	100	99.88
White Roof	93.2	99.86
Overall Acc.	89.02 %	
Kappa	0.88	

The overall accuracy of 90.42% and Kappa coefficient of 0.89 were estimated for test area 1, whilst overall accuracy of 80.83% and Kappa coefficient of 0.78 were calculated for test area 2. For test area 1, the highest producer's (99.93%) and user's (100%) accuracies were achieved for pools class. For test area 2, the highest producer's (100%) and user's (99.88%) accuracies were estimated for water class. Moreover, thematic maps produced with 10x10 superpixel size for both test sites were presented in Figure 3.



(a) (b)

Figure 3. Classification results for superpixels created for (a) test area 1 (b) test area 2.

While most classes were delineated from each other, it was observed that some classes were mixed up with each other and there were difficulties in distinguishing these classes with applied superpixels and the classifier. To be more specific, concrete and water classes were not clearly delineated each other in test area 1, whilst red roof-soil and pasture-forest classes had not clearly separated each other in test area 2.

5. CONCLUSIONS

Segmentation strategies using superpixel methods in remote sensing have become more popular in recent years. One of the most significant advantages of superpixels is that the most superpixel algorithms are available in open source implementations. In particular, the SLIC superpixels could be used for fast and accurate thematic mapping. In order to produce better quality superpixel sizes, the parameters to be used in the segmentation should be set properly. Using the specified work diagram, different SLIC superpixel sizes were produced and segmentation quality analysis was performed on two VHR images. Optimal SLIC superpixel parameters were determined according to five discrepancy measures. In this context, four SLIC superpixel sizes evaluated ranging from 5x5 to 20x20. It was observed that smaller superpixels required higher computational time but they produced more consistent image objects compared to reference objects. To sum up, initial size of 10×10 pixels for the superpixels offer consistent segments for extraction of ground objects. Furthermore, the SLIC superpixel approach has great potential to improve the automation of remote sensing data analysis and processing. Further research is required to investigate the robustness of the method and its parameter setting on different datasets.

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