

EVALUATION OF SATELLITE IMAGE SEGMENTATION USING SYNTHETIC IMAGES

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ABSTRACT

The segmentation stage is a key aspect of an object-based image analysis system. However, the segmentation quality is usually difficult to evaluate for satellite images. The Synthetic Image TEsting Framework (SITEF) is a tool to evaluate and compare image segmentation results. This paper presents an example of the use of SITEF for the evaluation of a segmentation algorithm, using a SPOT HRG satellite image with 6 vegetation land cover classes identified in an agricultural area. The segmentation results were evaluated under various perspectives, including the parcel size and shape, the land cover types, and the parameters used in the segmentation algorithm.

Index Terms— Image processing, Image segmentation

1. INTRODUCTION

The number of high and very high spatial resolution images acquired by Earth Observation Satellites (EOS) has increased considerably in recent years. One of the most challenging tasks in Remote Sensing at present is how to handle the huge amounts of image data made available, in order to extract meaningful information. The traditional pixel based approach, treating each image pixel individually without regard to its location in the image, is not a satisfactory approach, for at least two reasons: (1) the context information of a pixel (its neighborhood) is ignored; (2) the pixel is not considered to be a “natural” element, or a true geographical object [1], of an image scene.

It has been recognized that satellite image classification accuracy can be improved by modeling the spatial interaction between pixels, using Markov Random Field models [2]. Another alternative to the standard per-pixel analysis of multi-spectral EOS images is the so called the Object-Based Image Analysis (OBIA) approach. Instead of focusing on individual pixels, the OBIA approach consists of partitioning an image into meaningful image-objects, based on the similarity of neighboring pixels. A common element of all OBIA systems is the segmentation stage, where the image is partitioned in a number of objects (or segments). The segmentation is a critical stage of the OBIA process because if it fails to identify as an object a given

element present in the image, the subsequent stages will generally be unable to recognize (or classify) this element.

The evaluation of the segmentation stage is thus an important, yet often neglected, aspect of the OBIA approach. The main reason for this is the lack of a practical standard procedure for the evaluation of the segmentation results produced for EOS images [3]. The general process for segmentation evaluation is based on discrepancy measures between the segmentation result and a reference [4], but it is usually difficult to have abundant reference segmentation data in the case of EOS images.

The purpose of this work is to test if the Synthetic Image TEsting Framework (SITEF) [5] is an effective alternative, for EOS images, to the standard evaluation based on the identification of reference parcels (objects).

2. METHODOLOGY

The SITEF evaluation of image segmentation results is based on the production of multi-spectral synthetic images with the spectral characteristics extracted from a signature EOS image [5]. The knowledge of the shape and location of the objects in the synthetic image provides a reference, allowing for a quantitative evaluation of the segmentation results. The method was first presented in [5], using the Hammoude metric and the Rand, Corrected Rand and Jaccard external similarity indices. An improvement of the synthetic image generation process was presented in [6], to include adjacency effects between neighboring parcels.

The Hammoude metric evaluates the similarity between two segmentations proposed for an object (X and Y), by comparing the number of common and non-common pixels in the two segmentations [6]. It is computed by

$$H = \frac{\#(X \cup Y) - \#(X \cap Y)}{\#(X \cup Y)} \times 100 \quad (1)$$

where X and Y are two binary representations of the segmented object, and the operator $\#$ returns the “number of pixels ON” of a binary image [7]. The Hammoude metric, in the form presented in (1), has values between 0 and 100, with a value of 100 occurring when there is no intersection between segmentations (completely dissimilar), and a value of 0 when the two segmentations are equal.

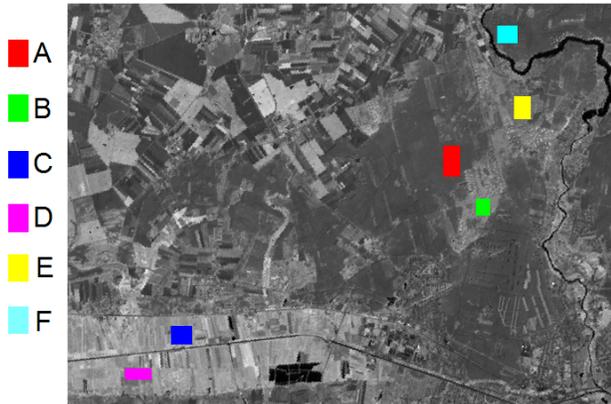


Fig.1 – Signature image with 6 land cover types.

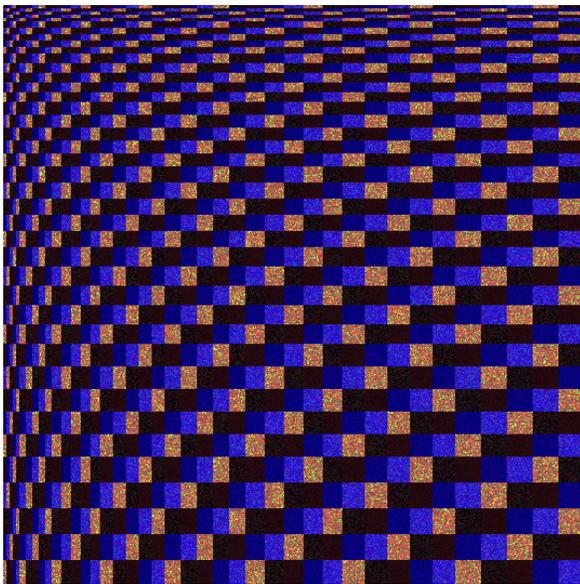


Fig.2 – Synthetic image for 5 classes (all except D).

Using SITEF, the evaluation of segmentation results can be done with three different perspectives: (1) for various parameter settings used in the segmentation algorithm; (2) for different parcel sizes and shapes; (3) for different land cover types (or spectral signatures) and sets of cover types.

2.1. Experimental setup

A SPOT HRG satellite image was used for the practical test carried out. The image covers a rural area of Poland, where 6 land cover types were identified (A – coniferous forest, B – deciduous forest C – mown grassland, D – non-mown grassland, E – gardens, F – clear cuts). A total of seven synthetic images were produced – one using all 6 classes, and six other using all 5-class sub-sets. Each synthetic image has 1600 parcels, from 1 by 1 to 8 by 8 units, with an unit of 3 by 3 pixels.

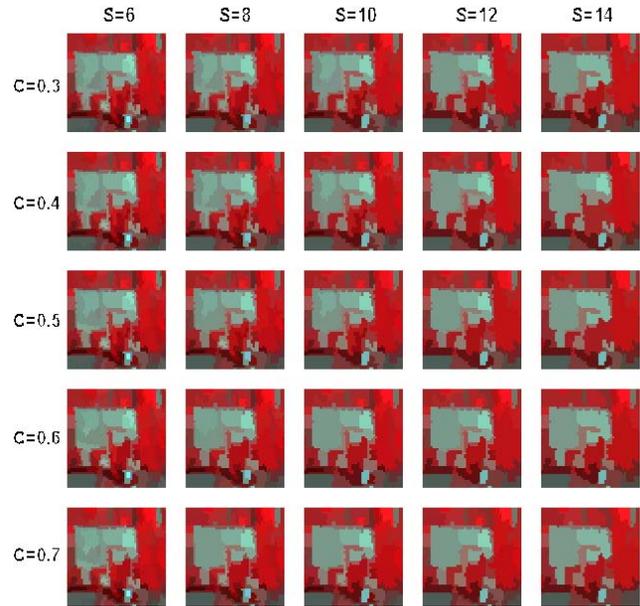


Fig.3 – Segmentation results for a section of the satellite image, with different values for the parameters S and C.

Figure 1 shows the near infrared spectral band of the satellite (signature) image with the training areas for the six land cover types tested. Figure 2 shows an RGB color composite of SPOT HRG bands 123 of one of the synthetic images created with 5 classes (all except D).

The original satellite image and the synthetic images created were all segmented using the multi-resolution algorithm in Definiens 7 software [8], with various values for the parameters S (Scale), C (Compactness) and M (Homogeneity, labeled as H in [8]).

The segmentation results provided by the segmentation software were compared with the expected (ideal) segmentation, using the Hammoude metric [5] for the 1600 parcels (objects) on each synthetic test image. A number of land parcels were also identified (manually) in the satellite image, to be used as reference.

3. RESULTS

The segmentation evaluation can be done through multiple perspectives, such as: parcel size and shape, land cover type of a parcel and its neighboring, and for the various parameter settings used in the segmentation algorithm. The segmentation results vary considerably with the parameter settings, as illustrated in figure 3 for a section of the satellite image, segmented with different parameter values for S (Scale) and C (Compactness), keeping the Homogeneity parameter M fixed at 0.5. It is thus difficult to select the most suitable set of parameter values for a segmentation.

A fraction of the synthetic image segmentation results are presented in figures 4, 5 and 6, where the average

Hammoude value (H) for sets of parcels with a common characteristic are plotted as a function of the segmentation algorithm parameter S (Scale), with the other parameters fixed (C=0.5, M=0.5). The values of H are presented in a range 0-100, with 0 corresponding to a perfect result (exact match between segmentation and reference).

The plot in figure 4 shows the average H for all parcels with the same land cover type, as a function of S. The best value for S is not the same for all classes. For land cover classes A, B and E the best is S=8, for class F the best value for S is 10 and for class C the best is S=14. The dotted line corresponds to the overall average, which has a minimum H of 8.01 for S=10.

The plot in figure 5 shows the average H for square shaped parcels of different sizes (1x1 to 8x8 units). For very small parcels (a single unit, or 3x3 pixels), the values of H become very large as S increases (47, 70, 71 and 96 for S=8, 10, 12, 14). Generally, for larger the parcels higher values of S are favored. For example, for parcels of 3x3 unit size the best S is 6, for 5x5 the best S is 10 and for 8x8 the best is having S=14.

The plot in figure 6 shows the average H for parcels of roughly the same area (15 or 16 square units) but different shapes (4x4, 3x5 and 2x8 units). For square or nearly square (3x5) shapes the best value for S is 8 while for the rectangular parcels of 2x8 it is best to have S=10.

The results presented in figures 4, 5 and 6 clearly show that the best choice for S depends both on the land cover type and on the parcel shape and size. There is therefore not an obvious choice for this parameter, unless the characteristics of the parcels of interest are well known. The same happens for the other segmentation parameters tested (C and M).

TABLE I. VALUES OF H FOR 5 TEST PARCELS SEGMENTED WITH DIFFERENT PARAMETERS (C, M, S).

	P1	P2	P3	P4	P5
C=0.3	0.505	0.800	0.448	0.706	0.511
C=0.4	0.514	0.611	0.435	0.607	0.474
C=0.5	0.505	0.444	0.435	0.512	0.372
C=0.6	<u>0.432</u>	0.444	0.435	0.696	0.417
C=0.7	0.495	0.444	0.448	0.590	0.404
M=0.1	0.505	0.444	0.435	0.512	0.372
M=0.3	0.514	0.777	0.745	0.575	<u>0.337</u>
M=0.5	<u>0.407</u>	0.661	<u>0.428</u>	0.481	0.354
M=0.7	0.526	0.632	<u>0.576</u>	<u>0.420</u>	0.621
M=0.9	0.856	0.887	0.816	0.792	0.580
S=6	<u>0.418</u>	<u>0.355</u>	0.584	0.717	0.469
S=8	0.432	0.444	0.584	0.645	0.372
S=10	0.505	0.444	0.435	0.512	0.372
S=12	0.505	0.444	0.435	0.512	0.372
S=14	0.505	0.937	0.435	0.512	0.372

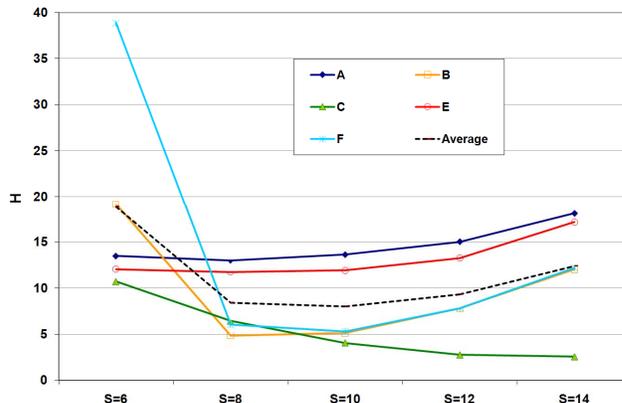


Fig.4 – Average H for different values of S, for fixed land cover type.

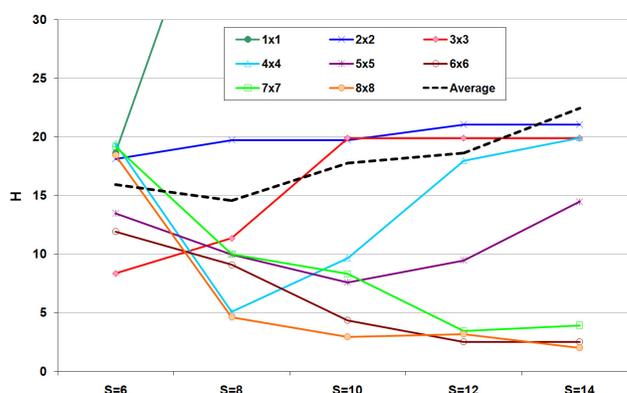


Fig.5 – Average H for different values of S, for different parcel sizes (square shape).

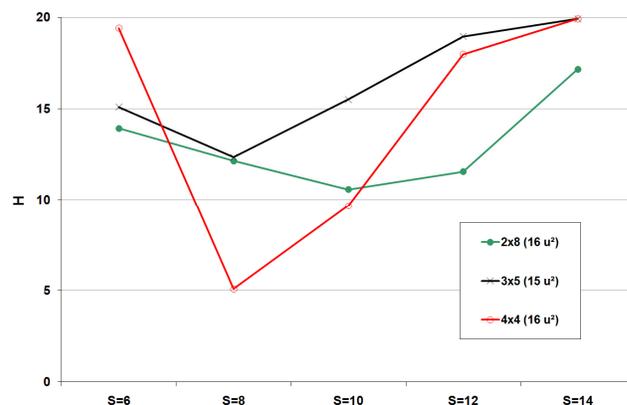


Fig.6 – Average H for different values of S, for fixed parcel size and different shapes.

The values of H for 5 test parcels, identified manually on the satellite image, are presented in Table I. The reference parameters used were C=0.5, M=0.1 and S=10. Each of these segmentation parameters was allowed to change within 5 values, with the other two parameters fixed (at the reference values). The best result for each parcel is underlined in the table, unless it is the reference value

(presented in bold). The values of H are generally high, which indicates an inability of the segmentation algorithm to segment the parcel in the same way as the human operator. There is nevertheless some differences in H as the parameter settings are changed, which indicate that some parameter tuning can be beneficial, as long as there is a representative set of reference parcels. This is of course not to be expected in most practical applications of EOS data.

4. CONCLUSIONS

The evaluation of satellite image segmentation results based on synthetic images offers obvious advantages. A large number of parcels is available in a synthetic image to evaluate the performance of a segmentation method. It can also provide multiple perspectives for the evaluation – e.g. parcel size, shape, land cover type, neighborhood parcels. The main disadvantage is that currently only rectangular shapes are used. However, the alternative using reference parcels identified on a EOS image is a laborious process and provides very limited possibilities for evaluation.

The evaluation of satellite image segmentation results based on the SITEF provides multiple perspectives that can assist in the selection of the most suitable segmentation algorithm or to fine tune its parameters. The practical experiment presented shows the potential of the method and the importance of various aspects for the segmentation result. The SITEF software is available for public use at www.fc.up.pt/sitef.

5. AGNOWLEDGMENTS

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