LAND COVER MAPPING BY AN OPTIMISED OBJECT-ORIENTED APPROACH. CASE OF STUDY: MEDITERRANEAN LANDSCAPES

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ABSTRACT

Remote sensing information from spaceborne and airborne platforms continues to provide valuable data for different environmental monitoring applications. In this sense, high spatial resolution imagery is an important source of information for land cover mapping. For the processing of high spatial resolution images, the object-based methodology is one of the most commonly used strategies. However, conventional pixel-based methods, which only use spectral information for land cover classification, are inadequate for classifying this type of images. This research presents a methodology to characterise Mediterranean land covers in high resolution aerial images by means of an object-oriented approach. It uses a self-calibrating multi-band region growing approach optimised by pre-processing the image with a bilateral filtering. The obtained results show promise in terms of both segmentation quality and computational efficiency.

INTRODUCTION

The uncontrolled urban development brings about unexpected and unwished environmental changes. Particularly, the Mediterranean landscape is a good example because it has been under serious and continuous anthropogenic pressure since historical times. The information obtained from a wide range of satellite sensors, as well as airborne sensors are extensively used for land cover mapping, that emerges for various purposes, among others, to deal with problems that arise as a result of human impact on natural landscapes through urbanisation and agricultural expansion.

The co-existence of built-up structures, vegetation, bare soil or water areas, and the high dissimilarity of functions like industrial or residential areas, as well as parks or agricultural regions can cause problems to discriminate the land covers (1). Moreover, the existence of undulating relief, a common feature of Mediterranean landscape, increases the spatial reflectance variability, thus introducing extra limitations to a conventional land cover classification.

The continuing advancements in satellite and aerial sensor technologies have increased the resolution of the obtained images. The benefit of high resolution imagery is that it allows, through the use of a variety of analysis methods, the extraction of more detailed and accurate information than is possible with lower resolution imagery. Although the information content of an image increases with spatial resolution, the accuracy of land cover/use classification may decrease due to an increase in within-class variability, which is inherent in a more detailed image (2).

In this sense, the object-based methods have become one of the most commonly used strategies for processing of high resolution imagery with many successful case studies reported (3). Considerable literature has compared object-based approaches with traditional pixel-based classification methods (4,5). Many of the studies found that the object-based methods generally produced higher classification accuracies compared to the pixel-based methods.

A prerequisite to object-based image analysis (OBIA) is image segmentation, which is normally defined as the subdivision of an image into separated regions (6). Traditionally, segmentation methods can be divided into methods based on pixel, on edge, and region-based methods (7). In the first kind of segmentation methods an image is segmented using several threshold values selected through image histogram inspection either manually or automatically. On the other hand, region-based image segmentation approaches, including region growing, region splitting, region merging, or their combinations, group spatially connected pixels into homogeneous segments. Finally, an edge-based segmentation first detects edges within an image, and then applies additional steps to produce a closed curve or boundary to complete the segment.

Numerous algorithms have been developed for image segmentation. A world famous example of object-oriented image analysis software is eCognition (8), in which the multi-resolution image segmentation method (9) is a key and patented technology.

This research presents a new designed and implemented image segmentation method, and results when this methodology is applied to characterise Mediterranean land covers. The results of the object-based approach obtained from segmentation with and without filtering are compared with the ones obtained from a classical pixel-based classification.

METHODS

Scene study

A geographical area placed in the Madrid Community (Spain), which corresponds to a Mediterranean ecosystem forest principally composed by oaks, bushes and meadows, was investigated. Three selected scenes have been studied in this research. They represent three degrees of Mediterranean landscape degradation: low (rural), medium (semi-rural) and high (build-up). In the scenes that present total and partial degradation, built-up structures and road infrastructures, industrial or residential areas coexist with extensions of natural Mediterranean forest.

Each true-colour aerial image has a spatial resolution of 0.5 m and covers an area of the order of 262 km^2. The top left corners of these images are placed at 428684.92E/4473641.10N, 433630.01E/4473719.02N and 434308.58E/4473719.02N (UTM geographic coordinates, h30). Due to the low spectral resolution and high spatial resolution of the image, classifying the 3-band image alone can result in high confusion between classes.

Mediterranean species of vegetation coexist with natural meadows, bare soils and a set of generated covers by anthropogenic effects like asphalted paths of some new little cities with commercial and sport buildings. Twelve thematic classes have been supervised *in situ* and the labels assigned for the training areas have been: shadow, Mediterranean trees, Mediterranean bush, meadow, soil 1 (mixed area with vegetation and ground), soil 2 (bare soil), bright soil (sandy), urban 1 (roads), urban 2 , urban 3, urban 4 and urban 5 (these classes have roofs composed of diverse materials like ceramic, dark concrete/asbestos, medium tone concrete/asbestos, asphalt, metal, corrugated iron, plastic or glass). Urban or built-up land is comprised of areas of intensive use with much of the land covered by structures.

Method principle and steps

The methodology introduced in this paper includes three main steps. The initial step is to process the input image using an edge-preserving smoothing filter known as bilateral filter. The second step is an automatic image segmentation following a selection-evaluation strategy based on work proposed by Paglieroni (10). Finally, the last step is to classify the segmented image using a minimum distance classifier.

Bilateral filtering

This research proposes an initialisation step (Figure 1), where the image is processed with a bilateral filter (Figure 1c). Bilateral filtering is a non-linear filtering technique introduced by Tomasi (11), where the weight of each pixel is computed using a Gaussian in the spatial domain multiplied by an influence function in the intensity domain that decreases the weight of pixels with large intensity differences. Pixels that are very different in intensity from the central pixel are weighted less even though they may be in close proximity to the central pixel. Therefore, this filter is applied as two Gaussian filters at a localised pixel neighbourhood, one in the spatial domain, known as domain filter (Figure 1a), which smoothes homogeneous areas, and one in the intensity domain, known as range filter (Figure 1b), which controls the smoothing for preserving edges. The main advantage of using bilateral filter is the growth of large and homogeneous regions.

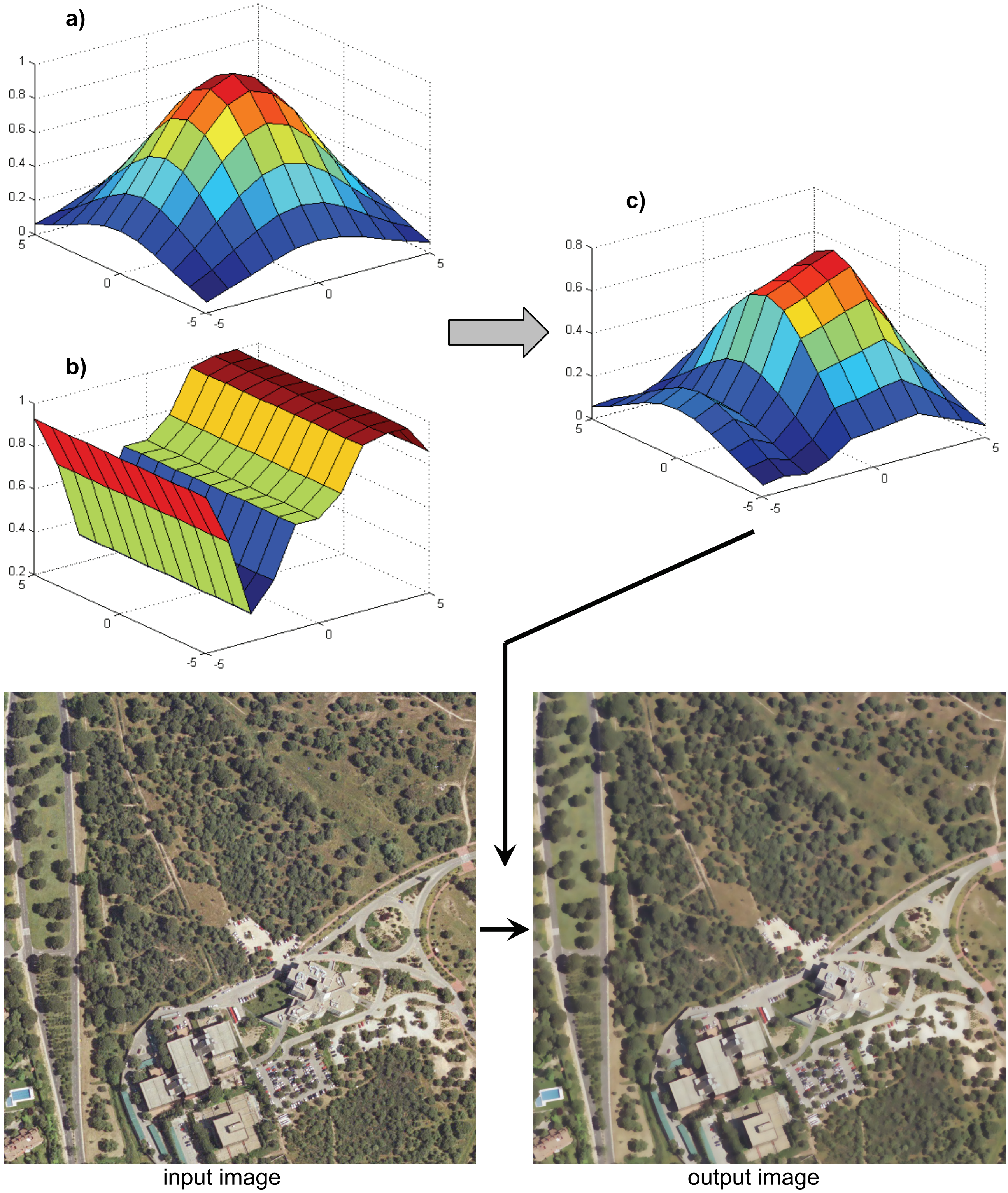

Figure 1: Pre-segmentation bilateral filtering scheme. a) Domain, b) Range and c) Bilateral filters.

Segmentation

The next step is to detect and extract the regions which compose the image. It should be noted that whatever method is adopted for the segmentation, a critical step is the selection of segmentation parameters. In most cases, these parameters are selected by trial and error.

On the other hand, based on the complementary nature of edge and region information, current trends on image segmentation wage for the integration of both sources in order to obtain better results and to solve the problems that both methods bear when used separately.

Taking into account all these considerations, a selection-evaluation approach based on growing and merging algorithms was utilised, because the authors believed it could produce more homogeneous segments than other types of image segmentation algorithms. This technique integrates edge and region information and provides a solution to traditional problems in region-based segmentation, such as setting appropriate parameters. The basic scheme of this approach is shown in Figure 2.

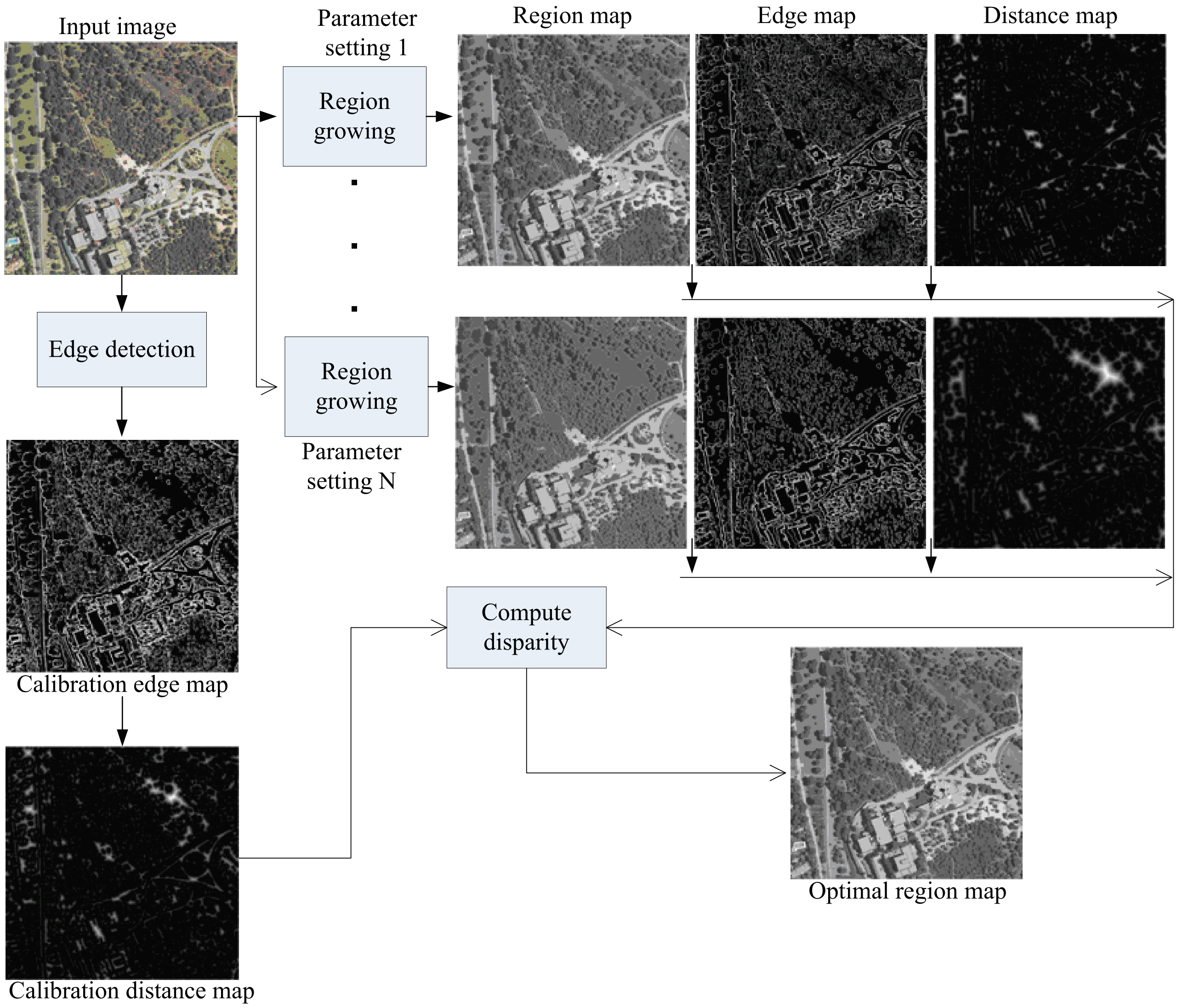

Figure 2: Methodological scheme. The edge information is used to evaluate the quality of a segmentation in order to choose the best segmentation from a set of region-based results.

In the first step, a calibration edge map is generated by applying an adaptive Canny edge detector (12). This edge map is used to define an evaluation function (Table 1) that evaluates the quality of the region based segmentation. The purpose is to achieve different results by changing parameters in the segmentation algorithm and then to use the evaluation function to choose the best results. Specifically the best region segmentation is the one where the region boundaries correspond most closely to the calibration edge map contours, therefore our evaluation function will be a measure of disparity between region maps and calibration edge maps.

Paglieroni defines this disparity measure by comparing the distance maps associated with edge maps of each region map obtained during the segmentation processes, with the distance map from the calibration edge map (Figure 2). Consider a region map R and an associated binary border map B in which pixels of value 1 correspond to borders between different regions. Let E be the calibration edge map with edge pixels of value 1 on a background of zeros. The disparity Δ_{BE} between R and E is given by Table 1, where n_B is the number of boundary pixels in B, n_E is the number of edge pixels in E, n_{BE} is the number of boundary pixels in B that are not associated with an edge pixels in E, and n_{EB} is the number of edge pixels in E not associated with a boundary pixel in B.

Table 1: Evaluation function. Disparity measure between region map and calibration edge map.

	Δ_{BE} (Disparity measure)
$n_B = n_E = 0$	0
n_B or $n_E = 0$ but not both 0	1
$n_B, n_E \neq 0$	$(n_{BE} + n_{EB}) / (n_B + n_E)$

This task is critical for obtaining good results and for that reason we decided to use a highly tested and robust edge detection algorithm such as Canny, instead of the method proposed by Paglieroni. This algorithm works in a multi-stage process, which is summarised below. First, the image is smoothed by Gaussian convolution, then two-dimensional first derivatives are computed, the gradient magnitude (edge strength) and gradient direction are calculated. Traditionally, the second stage is the non-maxima suppression with the goal of obtaining one-pixel wide contours. Our approach does not perform this task because it is not critical for our goal and on the other hand the algorithm is less expensive to compute. The last stage is the hysteresis thresholding using two thresholds, low and high, with the goal of removing noisy maxima without breaking the contours. These thresholds are used for estimating the population minimum parameter which is used to avoid small regions.

Table 2: Region growing-merging pseudo-code.

Begin Region growing:
1. find seed pixel (not labelled and following a row-order)
2. label it:
2.1 seed_pixel = i
2.2 region_average = intensity (seed_pixel)
3. explore its eight neighbours (8-connected):
3.1 list = neighbours(seed pixel)
3.2 while (length(list) > 0):
remove first pixel y from L
if (euclidean_distance(y, region_average) < distance):
add y to L
y = i
update region average
Begin Region-merging:
1. find region r with number of pixels < population_minimum
2. list N = neighbours(r)
3. explore its neighbours regions looking for the most similarity r_min:
3.1 while (length(N) > 0):
remove first region r' from N
r_min = find_minimum(Euclidean_distance(r, r'))
4. merge(r, r_min)
End

After generating the calibration edge map, the next step is to obtain the region maps using a region growing-merging algorithm. The starting points of the segmentation, known as 'seed' pixels, have to be identified. These seeds are selected according to a scan of the image by rows. The regions are built around these pixels by joining the similar neighbouring pixels to them. In order to compute the similarity between pixels, the Euclidean Distance was used. This distance metric can be termed as similarity measure (13,14) and among all the image metrics, it is the most commonly used because it is inexpensive to compute, noise resistant (because it averages samples across all spectral bands), and reversible. Once the initial regions have been obtained, a merging process is performed in order to eliminate small regions. The complete procedure is summarised in Table 2.

Classification

Finally, the segments are classified and labelled by a Minimum Distance supervised method. The results are compared with the ones obtained by Maximum Likelihood supervised method, which uses a pixel-based approach.

As classifiers differ in the way they partition the data or feature space into classes the value of individual training cases and nature of an ideal training set for a particular application scenario may vary considerably (15). In order to evaluate the pixel-based and object-based classifications, two independent dataset were used: the first, for training the models, includes the same reference points which constitute a total of 1000 pixels visually interpreted from the original imagery, and the second, for testing, which constitutes 10% of the training dataset. The classification accuracy was obtained for both classification methods using a standard error matrix (16). Then, overall accuracy (OA) and the kappa index (K) were calculated to assess the whole accuracy of the classified maps, and the producer and user accuracies were used to interpret the success of each class.

RESULTS

Final results for pixel-based and object-based classifications are found in Figure 3. There are obvious differences between the final classified images. The object-based method generates a more spatially cohesive map, with none of the spurious pixel effects found with the pixel-based classified images.

The object-based classification produced the highest overall accuracy in two of the three cases; rural and semi-rural (Table 3). Also, it is observed that object-based classification has given the highest overall accuracy for filtered images.

Table 3: Accuracy parameters for pixel-based and object-based classification methods.

	Rural	**Semi-rural**	**Built-up**
Object-based classification (without bilateral filter / with bilateral filter)			
Overall accuracy	100% / 100 %	91.6 % / 95.8 %	88 % / 92 %
Kappa	1 / 1	0.91 / 0.95	0.86 / 0.91
Pixel-based classification			
Overall accuracy	87.94 %	87.38 %	93.46 %
Kappa	0.86	0.85	0.92

In the case of pixel-based classification (Table 4), Bright Soil has the highest accuracy because other parts of the image represent very different spectral information compared to this unit. Mediterranean Bush and Urban 4 represent lower accuracy; it could be explained by the high spectral variability of these classes which made it difficult to distinguish with pixel based method. On the other hand, for object-based classification, all classes have better or equal accuracy after bilateral filtering, except Urban 1. Mediterranean Bush and Urban 4 have improved considerably with object-based approach (100%).

Finally, it was found that in most cases (in terms of class type) the object-based approach has priority to pixel-based approach.


Rural
Semi-rural
Built-up
RGB images
Object-based classified maps without bilateral filter
Object-based classified maps with bilateral filter

Pixel-based classified maps

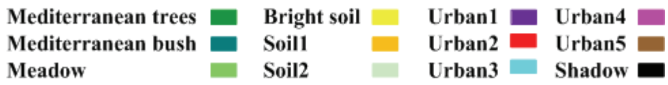

Figure 3: Comparison of object-based classified maps and pixel-based classified maps.

Table 4: Producer and user accuracies considering the three images.

	Producer accuracy	**User accuracy**
Object-based classification (without bilateral filter / with bilateral filter)		
Mediterranean trees	87 % / 100%	87 % / 87%
Mediterranean bush	100 % / 100%	100 % / 100%
Meadow	83% / 87%	71 % / 100%
Bright soil	100 % / 100%	100 % / 100%
Soil 1	87% / 100%	100 % / 100%
Soil 2	100 % / 100%	100 % / 100%
Urban 1	100 % / 100%	100 % / 87%
Urban 2	85 % / 100%	85 % / 85%
Urban 3	100 % / 100%	75 % / 100%
Urban 4	100 % / 100%	100 % / 100%
Urban 5	66 % / 66%	100 % / 100%
Shadow	87 % / 100%	100 % / 100%
Pixel-based classification		
Mediterranean trees	79.38 %	93.22 %
Mediterranean bush	83.33 %	40.74 %
Meadow	81.54 %	99.27 %
Bright Soil	100 %	99.66 %
Soil 1	99.63 %	91.58 %
Soil 2	96.97 %	94.81 %
Urban 1	73.86 %	96,29 %
Urban 2	99.64 %	82.55 %
Urban 3	79.06 %	100 %
Urban 4	66.67 %	97.78 %
Urban 5	100.00 %	86.29 %
Shadow	100 %	100 %

With the objective to evaluate this proposed segmentation methodology, the analysis of disparity factor (*1-similarity factor*) and the computation times have also been carried out (Table 5). Clearly, the execution time of the segmentation for the filtered images is lower than the no-filtered images, and this time it is highest in the built-up case. The similarity factor has similar values with and without filtering the original image.

Table 5: Evaluation parameters for segmentation method (without bilateral filter / with bilateral filter).

	Rural	**Semi-rural**	**Built-up**
Execution time (s)	6.469 / 4.187	9.313 / 5.625	11.328 / 7.547
Similarity factor	87% / 89%	90% / 90%	92% / 90%

CONCLUSIONS

A methodology based on a self-calibrating multi-band region growing approach optimised by a bilateral filter, has been proposed. It is obvious that it is very difficult to develop an automatic segmentation method which produces image segments of high quality for all images under examination (17), thus the parameters obtained by this methodology will often be used as a starting point of supervised process by the user. In this sense, the self-calibrating region growing is considerably useful for getting an initial segmenting image with a minimum contribution of the experts.

The suggested bilateral filtering provides good results on terms of segmentation quality and computation time.

The experimental results also indicate that object-based classification of the filtered images can improve the classification accuracy. Ideally, the same classification algorithm should be used in order to compare object and pixel based classification, but the results obtained by minimum distance algorithm in the pixel-based approach were bad and, on the other hand, our object-based segmentation software does not have an implementation of the maximum likelihood classifier because among all supervised classifiers, we believed that the minimum distance algorithm will produce better results due to the fact that this algorithm is very good when the values to be classified are completely different in nature, such as the attributes of objects generated in the segmentation.

In the future work, parallelisation possibilities of the self-calibration process and the bilateral filter will be studied for optimising the execution time on very large images.

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