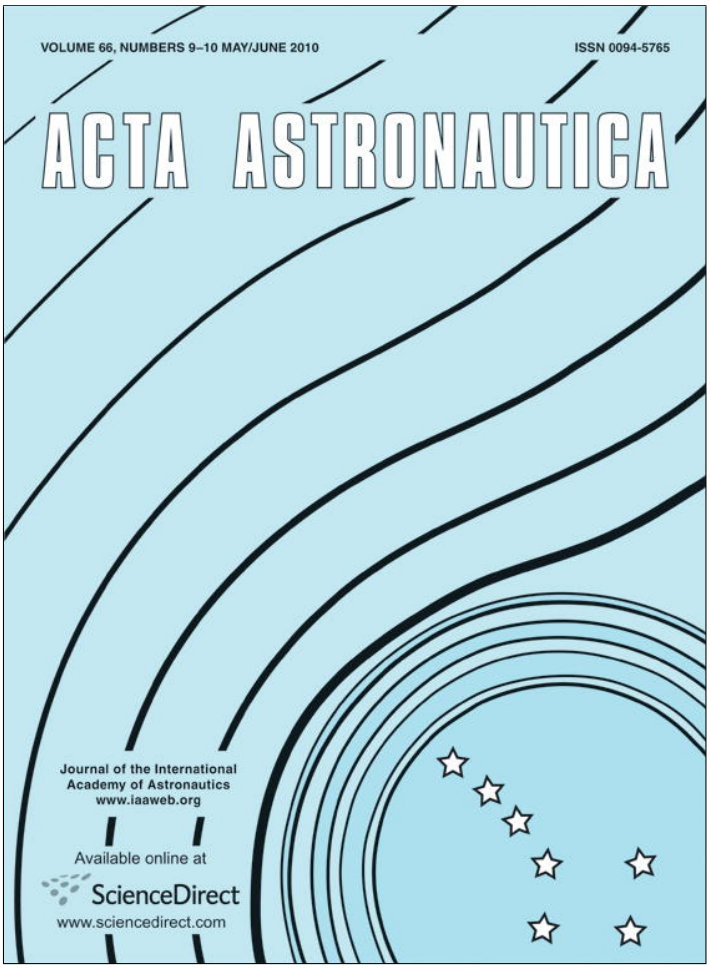

Acta Astronautica 66 (2010) 1302–1310

Contents lists available at ScienceDirect

Acta Astronautica

journal homepage: www.elsevier.com/locate/actaastro

Automatic archaeological feature extraction from satellite VHR images

Munzer Jahjah [a,*], Carlo Ulivieri [b]

[a] Sapienza, University of Rome, Dipartimento di Ingegneria Aerospaziale e Astronautica, Italy
[b] Sapienza, University of Rome, Centro Ricerca Progetto San Marco—CRPSM, Italy

ARTICLE INFO

Article history:
Received 30 January 2009
Received in revised form
23 September 2009
Accepted 24 October 2009
Available online 24 November 2009

Keywords:
Mathematical morphology
Pattern recognition
Segmentation
Feature extraction
Classification

ABSTRACT

Archaeological applications need a methodological approach on a variable scale able to satisfy the intra-site (excavation) and the inter-site (survey, environmental research). The increased availability of high resolution and micro-scale data has substantially favoured archaeological applications and the consequent use of GIS platforms for reconstruction of archaeological landscapes based on remotely sensed data. Feature extraction of multispectral remotely sensing image is an important task before any further processing. High resolution remote sensing data, especially panchromatic, is an important input for the analysis of various types of image characteristics; it plays an important role in the visual systems for recognition and interpretation of given data. The methods proposed rely on an object-oriented approach based on a theory for the analysis of spatial structures called mathematical morphology. The term "morphology" stems from the fact that it aims at analysing object shapes and forms. It is mathematical in the sense that the analysis is based on the set theory, integral geometry, and lattice algebra. Mathematical morphology has proven to be a powerful image analysis technique; two-dimensional grey tone images are seen as three-dimensional sets by associating each image pixel with an elevation proportional to its intensity level. An object of known shape and size, called the structuring element, is then used to investigate the morphology of the input set. This is achieved by positioning the origin of the structuring element to every possible position of the space and testing, for each position, whether the structuring element either is included or has a nonempty intersection with the studied set. The shape and size of the structuring element must be selected according to the morphology of the searched image structures. Other two feature extraction techniques were used, eCognition and ENVI module SW, in order to compare the results. These techniques were applied to different archaeological sites in Turkmenistan (Nisa) and in Iraq (Babylon); a further change detection analysis was applied to the Babylon site using two HR images as a pre–post second gulf war. We had different results or outputs, taking into consideration the fact that the operative scale of sensed data determines the final result of the elaboration and the output of the information quality, because each of them was sensitive to specific shapes in each input image, we had mapped linear and nonlinear objects, updating archaeological cartography, automatic change detection analysis for the Babylon site. The discussion of these techniques has the objective to provide the archaeological team with new instruments for the orientation and the planning of a remote sensing application.

* Corresponding author.
E-mail address: MUNZER@PSM.UNIROMA1.IT (M. Jahjah).

0094-5765/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.actaastro.2009.10.028

1. Introduction

Image analysis tasks that can be tackled by morphological operators include the following. (1) Image filtering: for noise reduction, edge enhancement and extraction/suppression of selected image structures, the selection depending on shape, orientation, and size criteria. (2) Image segmentation: for delineating the boundary of objects in grey-tone images or separating connected objects in binary images. (3) Image measurements: numerical values are computed for the whole image (or each segment produced by a segmentation procedure or even subwindows of fixed size) in order to characterize the texture, fragmentation, shape, orientation, or size of the image structures. The output measurements are then used for classification purposes.

These tasks are relevant to most applications dealing with EO imagery. It is therefore not surprising that many papers already report successful use of MM in geoscience and remote sensing [1].

The resulting multiresolution techniques (quadtrees, pyramids, fractal imaging, scale-spaces, etc.) all have their merits and limitations. For example, fractals have been exploited with great success in image compression but to a much lesser extent for segmentation problems. In the earliest multiresolution approaches to signal and image processing, the most popular way was to obtain a coarse level signal by subsampling a fine resolution signal, after linear smoothing, in order to remove high frequencies. A 'detail pyramid' can then be derived by subtracting from each level an interpolated version of the next coarser level. The emergence of wavelet techniques has considerably boosted the multiresolution approach. Unfortunately, application of wavelets to problems in image processing and computer vision is sometimes hindered by its linearity. Coarsening an image by means of linear operators may not be compatible with a natural coarsening of some image attribute of interest (shape of object, for example), and hence use of linear procedures may be inconsistent in such applications. Many of the existing morphological techniques, such as granulometries, skeletons, and alternating sequential filters, are essentially multiresolution techniques. In the processing and analysis of images it is important to be able to extract features, describe shapes and recognize patterns. Such tasks refer to geometrical concepts such as size, shape, and orientation [2].

Numerous feature extraction algorithms have been proposed for parametric classification. The Karhunen–Loeve transformation (principal component analysis—PCA) is optimum for signal representation in the sense that it provides the smallest mean square error for a given number of features, and can be used as a general feature extraction, and the features defined by this method are not optimum with regard to class separability [3]. These classic feature extraction algorithms such as (PCA) and linear discriminant analysis (LDA) have been extended to kernel principal component analysis (KPCA) [4] and kernel discriminant analysis (KDA) [5]. These methods have shown robust performance for image classification because it automatically supplies complementary discriminative information to the kernel feature space and improves class separability. Recently, nonlinear feature extraction algorithms based on a so-called kernel trick have appeared to reduce the limitations of linear feature extraction methods with respect to class discrimination.

Other methods such as the applied statistical procedure for interpreting texture were used by many scientists, e.g. the grey level co-occurrence matrix (GLCM), which is a widely used texture and pattern recognition technique in the analysis of satellite data [6,7]. Other texture extraction methods for retrieval are based on filtering or wavelet [8,9]. These methods measure energy at the output of filter banks as extracted features for texture discrimination.

Lee and Landgrebe [10] propose the decision boundary feature extraction algorithm that can take advantage of characteristics of neural networks that can solve complex problems with arbitrary decision boundaries without assuming underlying probability distribution functions of the data.

The following approaches work in the image domain by processing a single channel (or several channels in parallel) with specific structuring elements (sequential strategy).

Destival [11] applied the mathematical morphology for extracting objects such as roads, river networks, and village outlines. Pesaresi used a mixed morphological and spectral procedure to improve the accuracy of the built area classification from multisensor satellite data [12]. The opening and closing operations are performed by Chou et al. [13] to eliminate noise and small ice floes and to smooth boundaries in Landsat TM Antartic scenes. This improves significantly the segmentation/classification of complex scenes.

Morphological clustering in a feature space was first investigated where it is shown that a watershed-based classification performs better than a supervised maximum likelihood method for complex ground covers found on satellite images [14].

Alternating sequential filters using directional closings and openings [15] and directional morphological filters [16] were used for speckle removal on radar images and for road network extraction from SAR images consequently. Other methods such as directional morphological transforms to extract the relevant features of digitized topographic maps were used [17].

2. Mathematical morphology

In this approach, a signal/image is considered as a set of forms resulting from the intensity variations of a function that is defined in a one- or two-dimensional space. Mathematical morphology provides tools that allow extraction of the geometric elements and their spatial organization. The characteristics to be extracted may be lengths, heights, preferred directions or distributions. The location and quantification of these features are the first basic methodological results.

Morphological operations consist in transforming the initial image into another image with the aid of an

elementary geometric figure, called structuring element. In order to enhance some particularities the analysis takes into consideration connected entities, or forms, and not the points of the signal (image pixel) considered separately. Translations, unions, intersections or complementations are applied to the image. The structuring element determines the characteristics of the translations and therefore acts as a geometric probe to bring certain particular features of the image out. The present method consists of a particular sequence of these operations carried out with precise configurations of structuring elements [18].

The structuring element, which is generally symmetrical with respect to its origin point, is successively centred on each point of the definition space (image) of the signal and covers a certain domain of this space (windowing). The erosion consists in giving the origin point the lowest value taken by the function within the domain covered by the structuring element (this domain is called neighbourhood). On the contrary, the dilation consists in giving the origin point the highest value. By combining the two operations, opening is defined by an erosion followed by a dilation and closing by a dilation followed by an erosion. The openings and closings allow the location of singularities (peaks or valleys) whose width is less than that of the structuring element and thus reveals the signal undulations [19].

The methodology can be just as well applied to binary images (amplitudes are 0 or 1) as to grey tone images (amplitudes are integers between two extreme values). By means of pattern recognition processes and MATLAB, it allows a structural analysis of the images with a very short computer time and a reduced memory size. A further analysis is done using ENVI feature extraction module.

This methodology is applied to different archaeological sites (two-dimensional image analysis).

3. Pattern recognition

The eCognition SW is used as a further approach for structure analysis. It is based on an object oriented approach to image analysis. The basic difference to pixel-based procedures is that eCognition does not classify single pixels, but rather image object primitives that are extracted in a previous image segmentation step [20].

For this purpose eCognition features multiresolution segmentation, a patented procedure for image object extraction. It allows the segmentation of an image into a network of homogeneous image regions at any chosen resolution (Fig. 1).

These image object primitives represent image information in an abstracted form.

4. ENVI feature extraction

ENVI feature extraction is a module used as further approach for feature extraction; it is used for extracting information from high-resolution panchromatic or multispectral imagery based on spatial and spectral characteristics. It is possible to extract a wide variety of features such as vehicles, buildings, roads, bridges, rivers, lakes, and fields [21].

ENVI feature extraction uses an object-based approach to classify imagery (the same as eCognition SW). Traditional remote sensing classification techniques are pixel-based, meaning that spectral information in each pixel is used to classify imagery. The object in this module is a region of interest with spatial, spectral (brightness and colour), and/or texture characteristics that define the region. ENVI feature extraction is the combined process of segmenting an image into regions of pixels, computing attributes for each region to create objects, and classifying the objects (with rule-based or supervised classification) based on attributes, to extract features.

5. Area of study

The research area consists of the Babylon archaeological site, in the region of Al-Hilla south of Baghdad (Fig. 2). The site is located on the east part of the River Euphrates. The area is full of ruins and historical palaces (southern and northern buildings, Ishtar temple, ancient theatre, and Babylon tower) as long as modern buildings (ex Sadam palace). Along the southern side of the main palace, east of the river, there are some hills (around 60 m above sea level), which have figured significantly in these

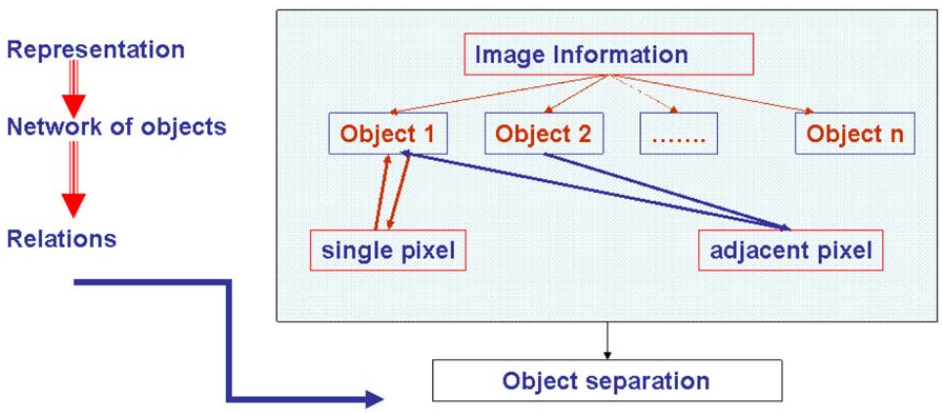

Fig. 1. Hierarchical network of image objects.

Fig. 2. The RGB image.

research activities since they are expected to be continuities of the Babylon settlements.

6. Remote sensing, pre- and post-elaboration of data

The remote sensing archive of high resolution data (QUICKBIRD 2002 and 2003) did not result in the best obtainable result if we consider the characteristics of the archived ones (sun angle azimuth and elevation), but they were sufficient, well detailed and without any cloud cover. The IKONOS 2005 was planned to be acquired possibly with the best geometry acquisition and no cloud cover. It was impossible to do the orthorectification without an accurate digital elevation model, to produce geometrically correct images for mapping and measurement; it was also impossible to visit the area to carry out the GPS campaign [22].

At that point we considered the information derived from the photo interpretation in 1986, with GPS field campaign, as correct and all the rest of the data were geo-corrected to it.

7. Development

7.1. Mathematical morphology approach

The very high resolution imagery (VHR) is characterized by high user interpretability, rich information content, sharpness, accuracy, high image clarity, and integrity. Although this kind of data diminishes the problem of allocating individual pixels to their most likely class, their rich information content dramatically aggravates the process of pixel labelling.

The automated allocation and extraction of real world geographic objects from HR sensed data were our objectives. Therefore we adopted the MM analysis using MATLAB functions. The area was divided into different archaeological zones to obtain better outputs and to enhance the border extraction; different parameters for each zone (rectangular, circular or linear segments or a mix of all) were taken for a better objects extraction.

7.1.1. Method

The RGB image (with enhanced spatial resolution using data fusion with the panchromatic band) was split or converted to its original bands [23]. The selected grey tone image was obtained using the Matlab image toolbox function called rgb2gray. This function converts an RGB image to greyscale image by eliminating the hue and saturation information while retaining the luminance or in other words converts the true colour image RGB to the greyscale intensity image. The grey tone image was pre-processed to evidence the required objects (e.g. archaeological segments) with respect to the background. To do that we used one of the Matlab morphological operations called IMADJUST that maps the values in intensity image to new values to increase the contrast of the output image. After that, the IIMHMIN operator was used to suppress all minima in the image whose depth is less than a determined value. The morphological reconstruction function (IMRECONSTRUCT) was applied to the grey image using as an input the results of IMOPEN and IMERODE functions with rectangular and square structure elements (Fig. 3) The enhanced greyscale image was divided into several parts (sector) with arbitrary size, then each of them was tested to the automatic detection of the objects that can potentially be archaeological segments or any other structures (buildings) [24].

The different archaeological shapes presented in the area forced us to divide the area into different zones and consequently different structure elements and parameters were used. The MM functions give the possibility of choosing a suitable structuring element in order to extract objects of any given shape, size, and orientation. This technique was tested within different archaeological shape segments using suitable flat structuring elements.

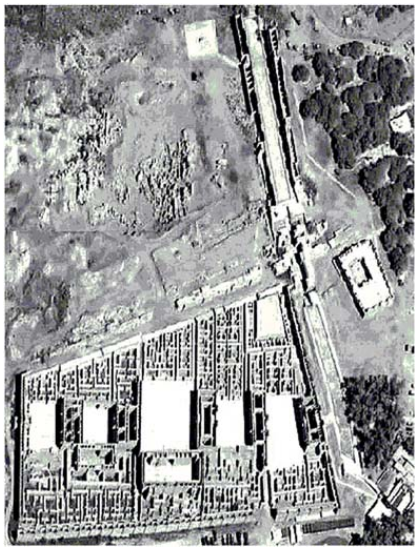

Fig. 3. Enhanced grey image used for morphological analysis.

Having the expected characteristics (length, width, and inclination), the morphological reconstruction process allows us to reconstruct the archaeological objects using the marker image on the mask image obtained by a binary process of the marker. The MM functions used could be summarized as follows: (1) BWAREAOPEN function with specific connectivity to eliminate the nondesired objects; (2) image skeleton: BWMORPH with a SKEL operation to remove pixels on the boundaries of objects; (3) IMERODE, IMERECONSTRUCT, and IMDILATE with a suitable structure element. Fig. 4 shows the step by step analysis flow diagram with the used MM functions.

7.1.2. Results

- First of all, in the main palace of Babylon, we extracted the main courtyard as shown in Fig. 5, then the internal walls as shown in Fig. 6. For the rest of the areas, the procedures were applied and the results are shown in Fig. 7.

The process is entirely automatic and there is no need of human operator. It is repeated for each area with different parameters and the results are posted over the original one. Some extra filters were used to enhance or remove the unwanted objects (errors due to the spectral mixing). The rest of the zones were processed with different parameters (Ishtar gate and Procession road in cyan colour, ruins "green and blue colour" as shown in Fig. 8).

As we can notice, that MM can be used for monitoring and documenting the preservation of the archaeological sites and the monumental areas. The MM functions not only map the extracted but also classify, describe shapes, and recognize patterns.

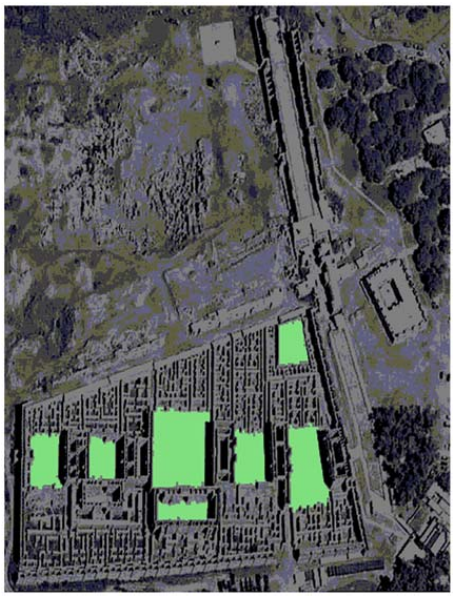

Fig. 5. Courtyard extraction.

Fig. 6. Internal wall extraction.

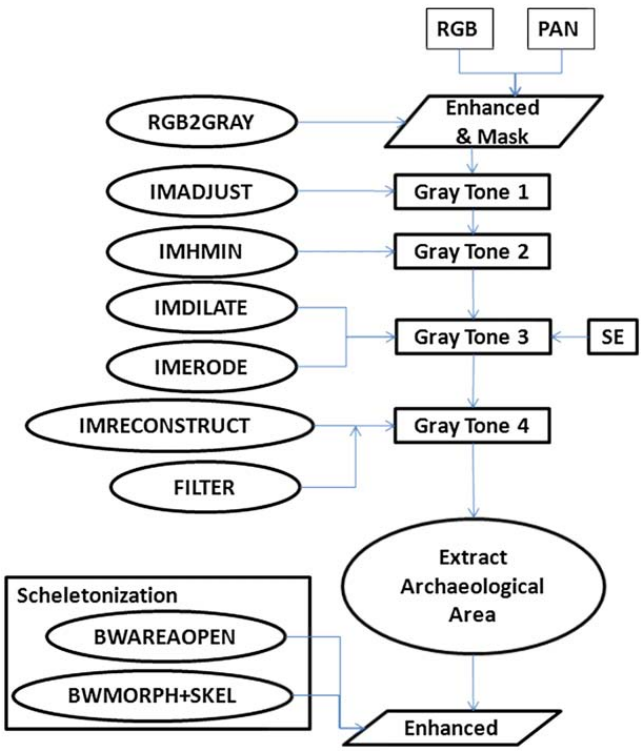

Fig. 4. MM functions flow diagram.

7.2. The eCognition approach

The procedure was divided in three image object levels.

Level 1 is used as a basis for the classification-based segmentation performed later on. Level 2 is the level in which the actual classification is to be performed and level 3 is the level in which the imported thematic layer (archaeological area) is to be analysed. The multiresolution segmentation of the three levels was done with different parameters in order to extract small and big objects (Table 1).

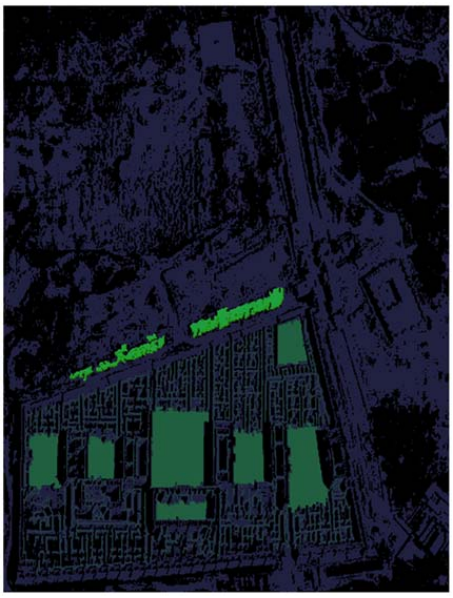

Fig. 7. Archaeological object extractions.

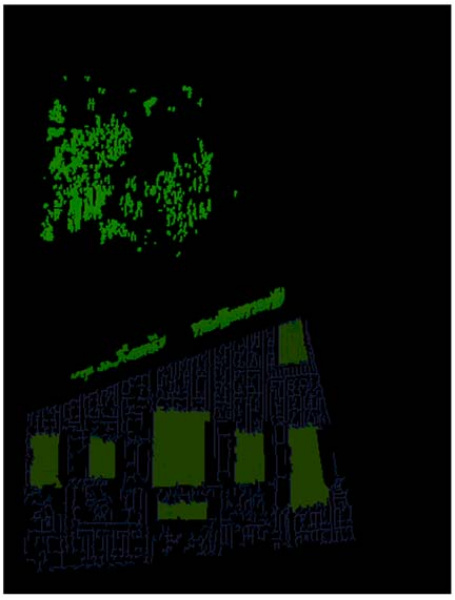

Fig. 8. Complete archaeological object extraction of Babylon.

Table 1
The parameters of the three levels used for multiresolution segmentation.

	Level 1	Level 2	Level 3
Scale	120	30	1000
Shape	0.7	0.3	0.7
Compactness	0.1	0.3	0.5
Smoothness	0.9	0.7	0.5

As a result of the segmentation procedure, the whole image is segmented and classified (Figs. 9 and 10), image objects are generated based upon several adjustable criteria of homogeneity or heterogeneity in colour and

Fig. 9. Segmentation of level 1.

Fig. 10. Classification based on segmentation of level 1.

shape as in the following formula:

$$f = wh_{colour} + (1 - w)h_{shape}$$

where w is the user defined weight for colour (against shape) with values from 0 to 1 [25].

7.3. ENVI feature extraction

We carried out two segmentation levels to extract the predefined segments; we faced problems such as over-segmentation in nonarchaeological areas (trees area). Merging is used in this approach to aggregate small segments within larger ones. Merging was very useful to delineate the boundaries in the two cases. The threshold value was chosen and controlled visually in order to delineate the boundaries of features as well as possible Fig. 11 shows the analysis ENVI flow diagram.

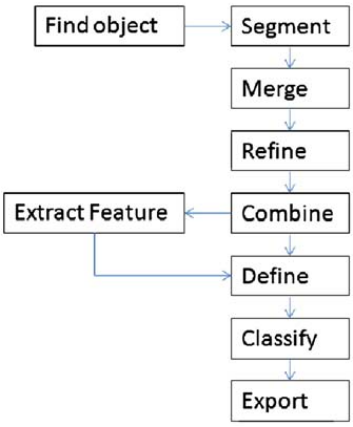

Fig. 11. Feature extraction workflow.

Table 2
The parameters of the two levels used for multiresolution segmentation.

	Level 1	Level 2
Scale	40	80.3
Merge	70	73.4
Threshold (refine)	230.809–255.000	32.23–138.52
Attributes computed	Spatial	Spatial spectral
Classification: rule-based	♯1: If area [615.68, 5387.48], then obj. belongs to "wide area" ♯2: If area [480.0, 679.4], then object belongs to "military camp"	If area <905.4030, then object belongs to "interior walls".
Smoothing	Threshold of 2	Threshold of 2
Result	Extract large areas	Wide area Military camp

Table 2 shows different values for different parameters used to extract different archaeological segments. In level 1 (Figs. 12 and 13) we extracted the large area (squares inside the south palace and military camp south of the southern palace of Babylon) choosing the suitable parameters using (rule based classification) 2 training data. The rule is built based on the spatial object attribute.

8. Comparison

Let us take the Nimrud archaeological site as an example for comparison (Fig. 14a and b). The MM used here is the same used for Babylon site feature extraction while for the ENVI module we used the following parameters (Table 3).

We can notice the differences between the two results due to different parameters and different methods but still we can noticed that the feature extraction can be considered as a classification fast method of small and large archaeological objects [26].

Fig. 12. Classification based on level 1 (spatial attribute only).

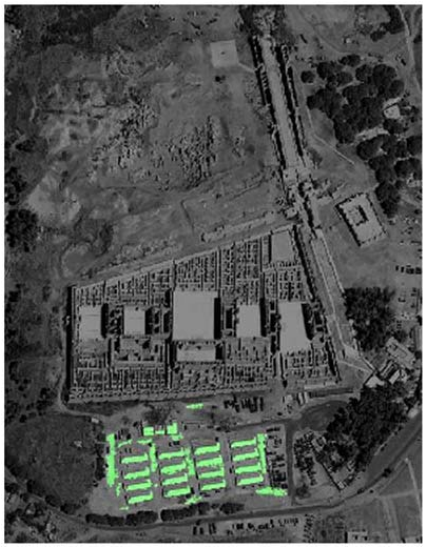

Fig. 13. Large area extraction.

9. Conclusion

The reason for using these techniques is that we are interested in measuring a property of real-world objects. Applying morphological operations on such HR images did reduce the errors in comparison with the results of the other two methods used (spatial and spectral classification).

Another result in using MM is the realization of a census of existing archaeological segments in a predefined zone.

The results, different archaeological elements, can be used, for example, for mapping the cultural heritage or can be used by decision makers. Comparing this output with other SW product such as eCognition and ENVI SW, we can notice first of all that the process is not automatic, because the intervention of the operator is necessary in the different segmentation levels, and many

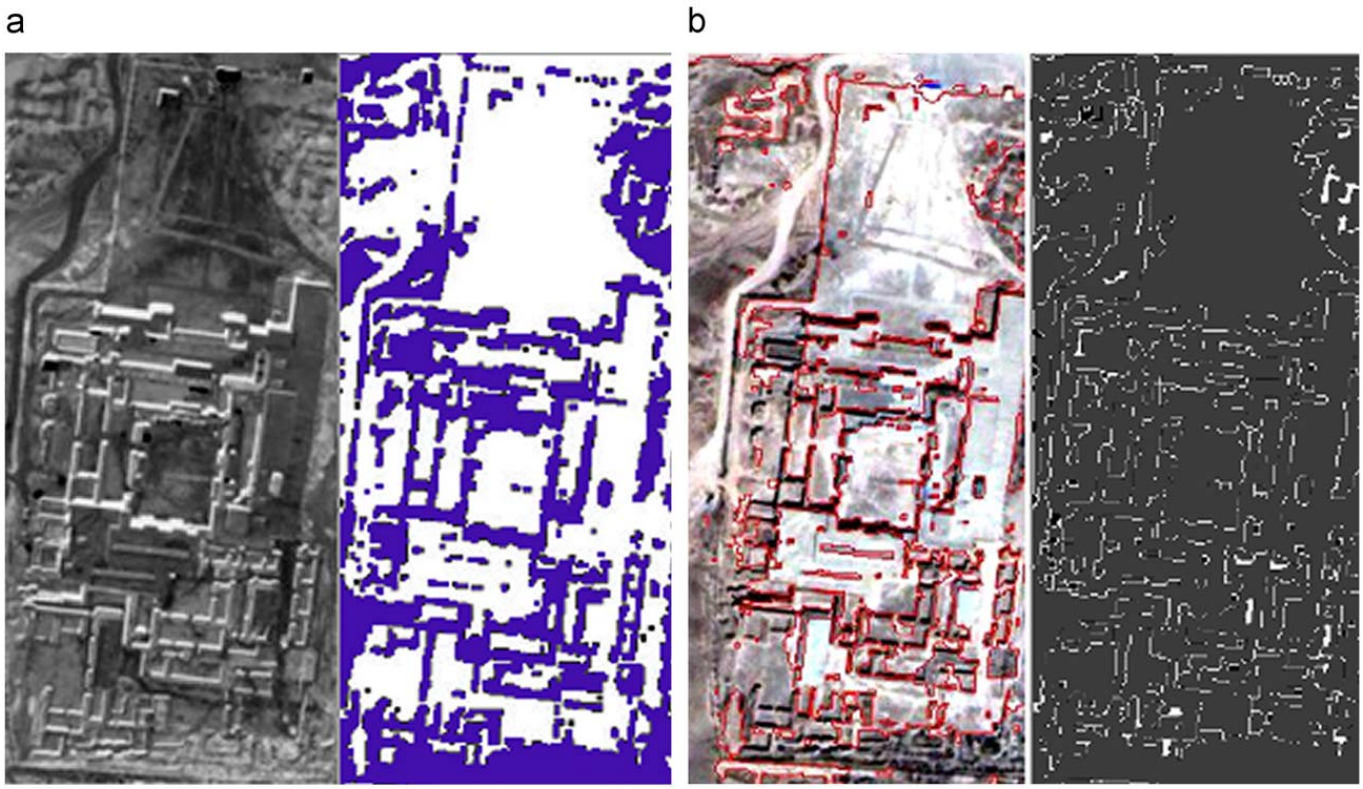

Fig. 14. (a) Comparison between MM and ENVI, left: Nimrud archaeological site. Right: feature extraction using MM (wide area). (b) Comparison between MM and ENVI, left: feature extraction using ENVI module (border extraction). Right: feature extraction using MM.

Table 3
The parameters of the level used for multiresolution Nimrud segmentation.

	Level 1
Scale	60
Merge	50
Threshold (refine)	No thresholding
Attribute computed	Spatial spectral texture color space
Classification: rule-based	♯1 (1.000): If maxband_1 [467.8225, 741.7195], then object belongs to "Feature_1" ♯2 (1.000): If bandratio [0.2642, 0.2744], then belongs to "Feature_1".
Smoothing	Threshold of 2
Result	Extract large areas

archaeological elements are misclassified or not well defined in terms of accuracy while in the MM method they are completely automatic.

Throughout this work we have seen how the MM functions can be applied to an accurate extraction of archaeological objects in an HR image. Such methodology can be considered as a noninvasive method for investigating and mapping objects especially in conflict zones.

Sharing technological resources made it possible to mainly focus the interventions in the planning and elaboration phases, with an immediate scientific repercussion of the initiatives realized. The integration of new methods and technologies in the archaeological field has evidenced the huge contribution in organizing, manipulating, and updating data.

References

[1] Pierre Soille, Martino Pesaresi, Advances in mathematical morphology applied to geoscience and remote sensing, IEEE Trans. Geosci. Remote Sensing 40 (9) (2002) September.
[2] Mathematical Morphology and Image Processing, ERCIM News No. 37—April 1999, Henk Heijmans.
[3] K. Fukunaga, W.L.G. Koontz, Application of the Karhunen–Loeve expansion to feature selection and ordering, IEEE Trans. Comput. C-19 (April) (1970) 311–318.
[4] B. Schölkopf, A. Smola, K.R. Müller, Nonlinear component analysis as a kernel eigenvalue problem, Neural Comput. 10 (5) (1999) 1299–1319 1998. IX, pp. 41–48.
[5] G. Baudat, F. Anouar, Generalized discriminant analysis using a kernel approach, Neural Comput. 12 (10) (2000) 2385–2404.
[6] D.G. Barber, E.F. LeDrew, SAR sea ice discrimination using texture statistic: a multivariate approach, Photogramm. Eng. Remote Sensing 57 (62) (1991) 949–958.
[7] Y. Zhang, Optimisation of building detection in satellite images by combining multispectral classification and texture filtering, ISPRS J. Photogramm. Remote Sensing 54 (1) (1999) 50–60.
[8] A. Laine, J. Fan, Texture classification by wavelet packet signatures, IEEE Trans. Pattern Recognit. Machine Intell. 15 (1993) 1186–1191.
[9] T. Randen, J.H. Husoy, Filtering for texture classification: a comparative study, IEEE Trans. Pattern Recognit. Machine Intell. 21 (1999) 291–310.
[10] Chulhee Lee, David A. Landgrebe, Decision boundary feature extraction for neural networks, IEEE Trans. Neural Networks 8 (1) (1997) January.
[11] I. Destival, Mathematical morphology applied to remote sensing, Acta Astronaut. 13 (6/7) (1986) 371–385.
[12] J. Serra, P. Soille (Eds.), Mathematical Morphology and its Applications to Image Processing—Poster Contributions, Paris, France, September 1994, pp. 43–44.

[13] J. Chou, R. Weger, J. Ligtenberg, K.-S. Kuo, R. Welch, P. Breeden, Segmentation of polar scenes using multi-spectral texture measuresand morphological filtering, Int. J. Remote Sens. 15 (5) (1994) 1019–1036.
[14] A. Watson, A new method of classification for Landsat data using the 'watershed' algorithm, Pattern Recognit. Lett. 6 (1987) 15–19.
[15] F. Safa, G. Flouzat, Speckle removal on radar imagery based on mathematical morphology, Signal Process. 16 (1989) 319–333.
[16] C. Mering, J.-F. Parrot, Radar images analysis using morphological filters, in: J. Serra, P. Soille (Eds.), Mathematical Morphology and its Applications to Image Processing, Kluwer, Norwell, MA, 1994, pp. 353–360.
[17] H. Yamada, K. Yamamoto, K. Hosokawa, Directional mathematical morphology and reformalized Hough transformation for the analysis of topographic maps, IEEE Trans. Pattern Anal. Machine Intell. 15 (April) (1993) 380–387.
[18] PIMM1, An image processing asic based on mathematical morphology, Ecole Nationale Superieure des Mines de Paris Centre de Morphologie Mathematique, J.C. Klein, R. Peyrard, IEEE CH 1234-5/89/00.
[19] Image Processing Toolbox, User Guide, MATLAB Version 9. The MathWorks, Inc., [2001–2003].
[20] eCognition User Guide, Copyright 2000–2004 Definiens Imaging.
[21] ENVI Feature Extraction Module User's Guide, ITTVIS 2008.
[22] M. Jahjah, A. Invernizzi, C. Ulivieri, R. Parapetti, Archaeological remote sensing application pre-post war situation of Babylon archaeological site—Iraq, J. ACTA Astronaut. 61 (2007) 121–130.
[23] R. Welch, W. Ahlers, Merging multiresolution SPOT HRV and Landsat TM Data, Photogramm. Eng. Remote Sensing 53 (3) (1987) 301–303.
[24] Irwin Scollar, Archaeological processing and remote sensing, Cambridge University, 1990 276–292.
[25] M. Baatz, A. Schäpe, Object-oriented and multi-scale image analysis in semantic networks, in: The Second International Symposium: Operationalization of Remote Sensing, New Methodologies, (1999) 16–20 August, ITC, NL.
[26] R.O. DUDA, P.E. Hart, D.G. Stork, Pattern Classification 2nd edition, 2001, pp. 9–17.