An object based approach for coastline extraction from Quickbird multispectral images

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Abstract— Because of the reduced dimensions of pixels, in the last years high resolution satellite images (Quickbird, IKONOS, GeoEye, …..) are considered very important data to extract information for coastline monitoring and engineering opera planning. They can integrate detail topographic maps and aerial photos so to contribute to modifications recognition and coastal dynamics reconstruction. Many studies have been carried out on coastline detection from high resolution satellite images: unsupervised and supervised classification, segmentation, NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index) are only some of the methodological aspects that have been already considered and experimented. This paper is aimed to implement an object based approach to extract coastline from Quickbird multispectral imagery. Domitian area near Volturno River mouth in Campania Region (Italy), an interesting zone for its dynamics and evolution, is considered. Object based approach is developed for automatic detection of coastline from Quickbird imagery using the Feature Extraction Workflow implemented in ENVI Zoom software. The resulting vector polyline is performed using the smoothing algorithm named PAEK (Polynomial Approximation with Exponential Kernel).

Keyword-Coastline detection, High resolution satellite images, Quickbird, Object based approach, Rule based classification.

I. Introduction

The coastal environment is a transition zone between land and sea: crucial element for both natural ecosystems and human activities, it is highly dynamic and subject to continuous changes [1]. The monitoring activity of this zone is an important task in national development and environmental protection; above all to detect coastline position in various times is a fundamental work and nowadays remote sensing technology plays a unique role for data acquisition as an economical method [2]. In fact to achieve this information is complex, difficult and time consuming when using traditional ground survey techniques; morphological characteristics of the coastline (sandy beaches, rock cliffs, etc) influence data acquisition and rapid as well as replicable techniques are required to monitor retreat or aggradation of coastline and update its position [3].

As reported by European Environment Agency, coastline (or shoreline) is defined as the line that separates a land surface from an ocean or sea. As the tide changes over time, shoreline position also changes with respect to shore profiles and tidal levels; for this reason the term "instantaneous shoreline" is typically used to indicate a certain state of the shoreline at an instant of time [4, 5]. Shoreline extracted from a satellite image is instantaneous shoreline.

Optical images have advantages such as easier interpretation and easier availability; furthermore, absorption of infrared by water and its strong reflectance by soil and vegetation make an ideal combination for mapping the spatial distribution of land and sea (as well as river, lake or ocean); for consequence the images that contain visible and infrared bands are extensively used for coastline mapping [2].

However also one single band can support coastline detection: for example Band 5 (1.567 μm -1.784 μm) of Landsat TM shows great differences of BV for land and sea because vegetation and soil reflect the energy in this range while water (especially if clear) absorbs it [6]. False color RGB composition (i.e. bands 543 for Landsat 7 ETM+) are used to support coastline manual extraction via visual interpretation. Automatic extraction is performed on the resulting image of unsupervised classification in which wet and dry pixels are distinguished [7]. Clustering algorithms such as ISODATA (Iterative Self Organized Data Analysis) are applied to satellite images such as Landsat 5 TM [8]. Pansharpening methods permit to extend geometric resolution of pan image to multispectral ones [9], so more detailed information can be acquired for coastline detection.

At present High Resolution images are largely used in many application fields of remote sensing because of the possibility they offer to accurately identify and contour objects and land covers. Pixel dimensions are reduced to less than 1 m and some authors define them Very High Resolution images. Contextually the numbers of bands tend to increase: WorldView-2 sensors include 8 bands and this enables remote sensing applications, ie land cover classification [10].

For high resolution satellite images automated extraction of the coastline is more complex because of the reduced pixel dimensions that require greater attention to distinguish different classes such as sea and soil. In this paper an object based approach [11, 12] is proposed for instantaneous coastline extraction from QuickBird dataset of Domitian area around the mouth of the Volturno River.

The satellite images are handled by the ENVI Zoom software with the main steps of segmentation and classification. Thus, vector coastline is obtained from object-based approach that is already applied for medium resolution images [13]; PAEK (Polynomial Approximation with Exponential Kernel) smoothing algorithm is carried out to render the feature more realistic.

II. MATERIALS AND METHODS

A. Study area

The considered area (Fig. 1) concerns Domitian zone around the mouth of the Volturno River in Campania Region (Municipality of Castel Volturno), Italy.

Fig. 1. Study area: territorial framework and RGB composition of multispectral files (Red, Green, Blue) of Quickbird imagery

The Domitian coastal zone is limited by Aurunci Mountains (North-West), Caserta city (North), Avella town (North-East) and Lattari Mountains (South). The Plio-Pleistocene coastal graben is filled by pyroclastic deposits of Roccamonfina and Campi Flegrei volcanic complexes and powerful layers of alluvial materials of the Volturno and Garigliano Rivers [14]. The study area has a temperate Mediterranean climate and the prevailing wave (70% frequency) comes from the west-northwest; rainfall is concentrated during autumn and winter and usually has its maximum in the months of October and December and minimum from May to September; the prevailing winds on the coast are those coming from the west and southwest [15].

B. Data set and early elaboration

In this application Quick Bird imagery [16] acquired in 2012 was used: dataset included one panchromatic image (pan: 760 - 850 nm) with spatial resolution 0.60 m, and four multispectral ones (blue: 450-520 nm; green: 520-600 nm; red: 630-690 nm; near-IR: 760-890 nm) with spatial resolution of 2.40 m; all data presented radiometric resolution of 11 bit. Imagery was ortho-rectified using Rational Polynomial Functions (RPFs) [15]: the cartographic coordinates (x, y) of Ground Control Points (GCPs) and Check Points (CPs) were acquired from the map elements of Campania Region (scale 1:5.000) and a Digital Terrain Model with 5 m was used for 3D information as required for RPFs application. The entire dataset was referred to the UTM WGS84 cartographic system. In addition, the images were atmospherically corrected using a dark object subtraction method [17, 18, 19, 20].

C. *Coastline extraction: segmentation*

A based object approach was adopted for coastline detection using Feature Extraction Workflow, implemented in ENVI Zoom software. An object is a region of interest with spatial, spectral (brightness and colour), and/or texture characteristics that define it. This methodology is the combined process of segmenting an image into regions of pixels, computing attributes for each region to be created and classifying the objects (with rule-based or supervised classification) based on those attributes, to extract features [21].

The Feature Extraction consists in two phases: FIND OBJECT; EXTRACT FEATURES.

The FIND OBJECT step begins with the image segmentation into pixels regions named objects. An image object is generally defined as a group of pixels sharing similar spectral and/or textural properties [22]. Segmentation splits an image into separated regions or objects [23]. Segmented objects are organized into image object levels also known as scale levels [24].

An image object level serves as an internal working area for object based image analysis [25]. The scale parameter controls the object size that matches the user's required detail level; it is considered the most crucial parameter of image segmentation: different levels of object sizes can be determined by applying different numbers in the scale function; the higher number of scale generates larger homogeneous objects (smaller scale – lower level of detail), whereas the smaller number of scale will lead to smaller objects (larger scale) [26]. A smaller number used in the scale parameter produces a higher level in the segmentation procedure. This situation is called over-segmentation. The decision on the appropriate scale level depends on the size of objects required to achieve the mapping goal [22]. The Scale Level values range from 0.0 (finest segmentation) to 100.0 (coarsest segmentation; all pixels are assigned to one segment). In this application, the best result was obtained using a scale level of 30.

The segmentation process produces an image (Region Means image) which consists of a raster file where each segment is characterized by the mean pixel value. The mean pixel value is calculated on the DN for several considered bands. ENVI Zoom uses an edge based algorithm to segment an image [27].

The Region Means image is subjected to the step of Merging Segments: it permits to aggregate small segments within larger areas where over-segmentation may be a problem. This operation is based on the Full Lambda-Schedule algorithm created by Robinson, Redding and Crisp [28]. The merge level parameter represents the threshold lambda value, which ranges from 0.0 to 100.0. The best result for this application was obtained using a merge level of 10 (Fig. 2).

Subsequently, in Computing Attributes step, spectral, spatial and texture attributes are defined for the object based classification [21].

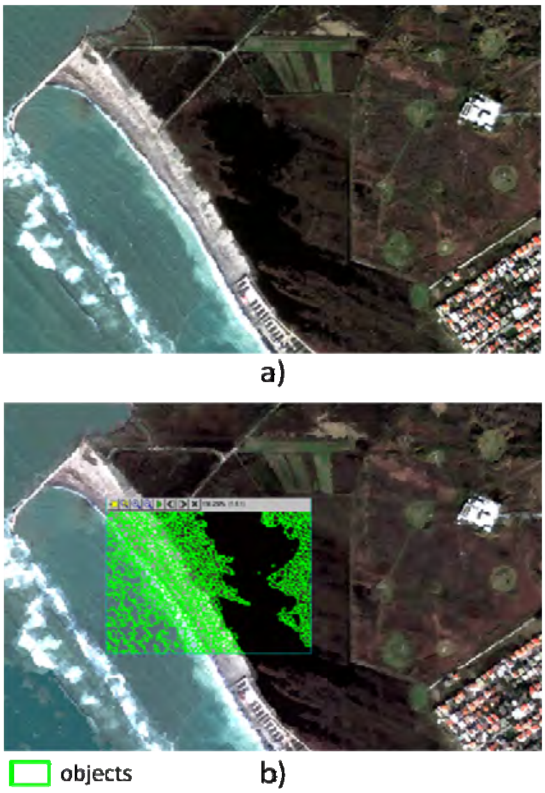


Fig. 2. a) Quick Bird multispectral images (RGB composite); b) segmented image.

D. *Object based classification - a rule based approach*

In EXTRACT FEATURES, the object-based classification is performed to assign the objects to a feature, using a rule-based approach. Rule-based classification is an advanced method that allows to define features of interest building rules based on object attributes (spatial, spectral and texture properties). Rule-building is primarily based on human knowledge and reasoning about specific feature type.

The traditional rule-based classification is centred on strict binary rules. Objects that are not conformable to all rules are not allocated and remain unclassified. In the Feature Extraction Workflow, besides the traditional ule-based method, a rule-based classification based on a Fuzzy Logic approach can be chosen. This approach does not use the strict binary rules, but it is based on a membership function (a mathematical concept for modelling the underlying data distribution) to represent the membership degree of an object to a feature type. Information extraction from remotely sensed data is limited by sensor measurements noise, signal degradation from image pre-processing, and imprecise transitions between land-use classes. Most remotely sensed images contain mixed pixels that belong to one or more classes. Fuzzy logic helps to relieve this problem by simulating uncertainty or partial information that is consistent with human reasoning.

The output of each fuzzy rule is a confidence map, where values represent the membership degree to the feature type defined by this rule. In classification, the object is assigned to the feature type that has the maximum confidence value. Two classes were considered for the classification: a class for water (WATER) and a class for everything that was not water (NO WATER). The rules definition was based on the estimation of thresholds for considered classes. These thresholds were derived from a careful analysis of the histograms of NDVI (Normalized Difference Vegetation Index). NDVI is function that varies in the range [-1, +1]. Negative values correspond to water, values close to zero but positive values correspond to soils and further, from 0.2 indicate the presence of surfaces vegetated with maximum values around 0.8 for very dense vegetation [17]. NDVI was used to better define the coastline location and calculated using the expression [1]:

$$NDVI = \frac{NIR - R}{NIR + R} \quad [1]$$

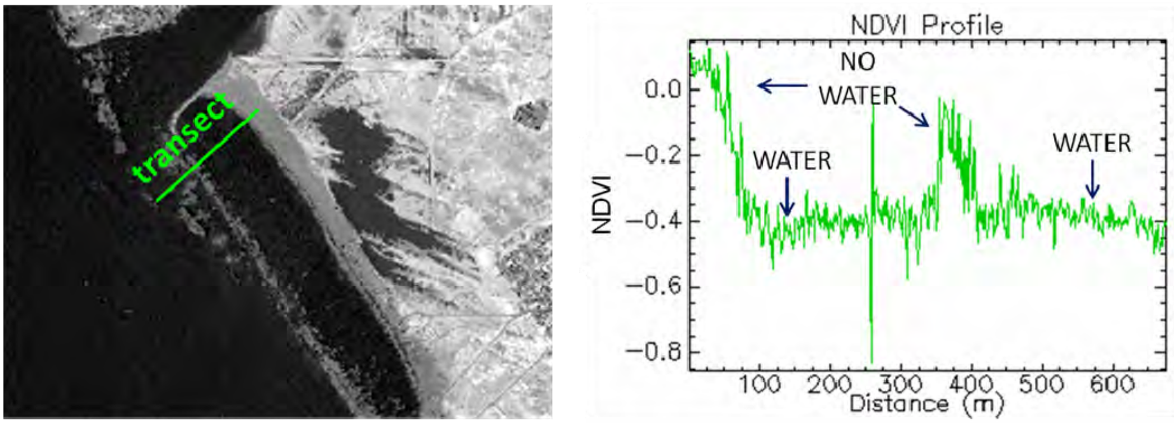
where

NIR = Near Infra-Red band

R = Red band

In Fig. 3, the NDVI profile along a transect which proceeds from the coast towards the sea is shown. The water takes on values less than that is not water in NDVI images [1]. To detect the thresholds the software supplies the possibility to view the resulting classification in real time so the user can change them to perform the output. In other terms the interactive visual analysis permits to optimize the performance.

The considered rules set are shown in the Table 1.



a) b)

Fig. 3. a) transect on NDVI image; b) NDVI profile.

TABLE I
Rules set for Quick Bird images classification.

	RULES
WATER	If avgband_NDVI < -0.1512 then object belongs to “WATER”
NO WATER	If avgband_NDVI > -0.0729 then object belongs to “NO WATER”

Avgband_NDVI is a spectral attribute and indicates an average value of the pixels comprising the region in NDVI [21].

The rule-based classification produced an image in which the water class appeared blue while everything that was not water appeared beige (Fig. 4 - b). The classification results were exported to a shape file (Fig. 4 - c).

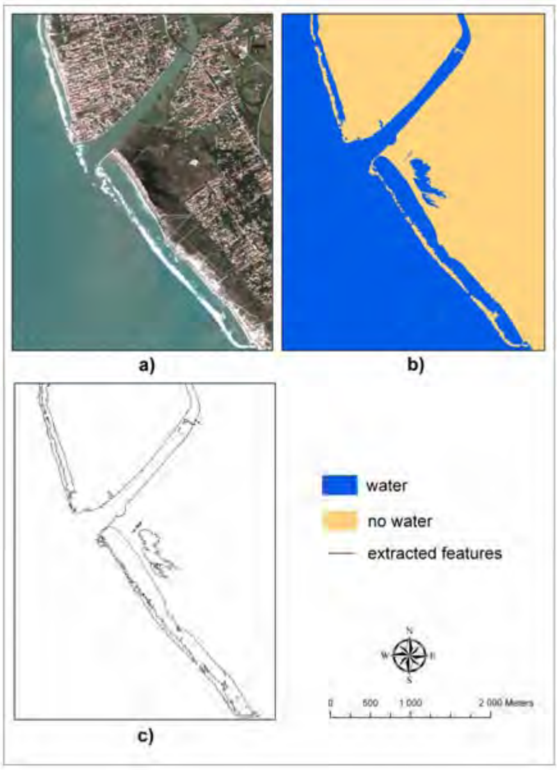


Fig. 4. a) Quick Bird multispectral image (RGB composite); b) classified image; c) extracted features.

E. Smoothing application in GIS environment

In GIS environment, the obtained shape file was processed by spatial analysis techniques. The spatial analysis made it possible to extract the polyline corresponding to the coastline. The coastline feature had a jagged pattern derived from the classification raster image. An operation of smoothing was carried out to improve the polyline aspect and to obtain a result that was closer to reality. Smoothing is a type of generalization operation [29] that removes points from a line to improve its aesthetic quality (Fig. 5). In this study, the best result was obtained by the Polynomial Approximation with Exponential Kernel (PAEK). PAEK is a smoothing algorithm [30] that calculates smoothed lines using a parametric continuous averaging technique. The current point coordinates are calculated by the weighted averaging of the coordinates of all points of the source line. The weights of each point decrease with the distance along the line to the current point. In addition, it is used an approximation with the second degree polynomials. The result depends on one parameter: smoothing tolerance. The smoothing tolerance specifies the length of a moving path along an input line used to calculate the smoothed coordinates by PAEK algorithm. The method is stable - a minor change to the parameter causes a minor change in the result [31]. In this application a smoothing tolerance of 10 units was used.

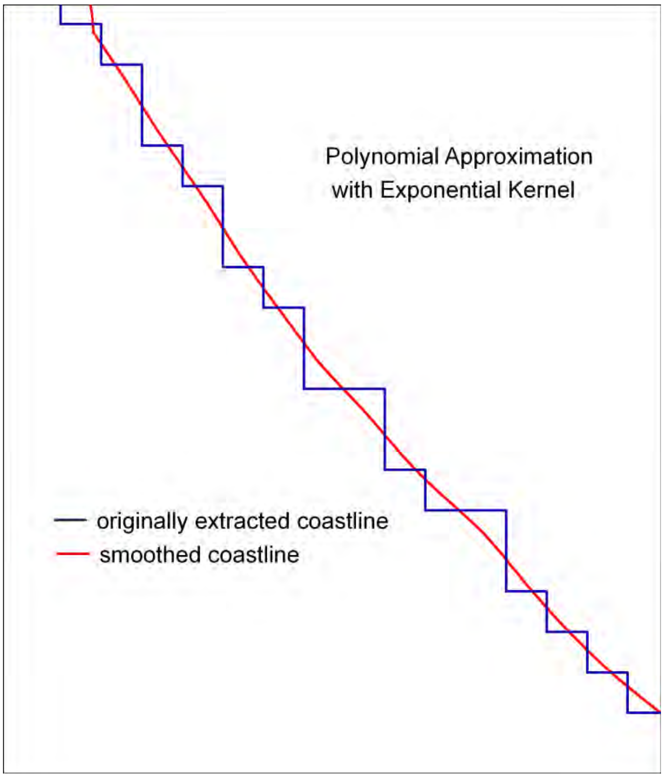


Fig. 5. The smoothing operation gives a more realistic trend for extracted coastline from Quick Bird data.

III. Conclusion

Object-based feature extraction process is very fast and feasible for the coastline detection in high resolution satellite imagery such as Quickbird, because it has similar results to those obtained using the manual digitization. ENVI Zoom software supplies possibilities to implement this approach: firstly segmentation is carried out using all multispectral bands of the satellite dataset, then classification is performed using both segmented image as well as NDVI map. The choice of appropriate values for scale and merge parameters of segmentation and the introduction of rules for the classification allow to discriminate accurately two classes: water and no water.

The definition of these different classes can be used to identify and extract the instantaneous coastline. The smoothing operation lets obtain a polyline congruous with the coastal profile, eliminating the jagged effect resulting from raster data. The Polynomial Approximation with Exponential Kernel algorithm, within ArcToolbox of ArcGIS, can be used for the smoothing.

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References

[1] J.A. Urbanski, “The extraction of coastline using obia and GIS,” ISPRS-GEOBIA, Ghent, Belgium, 29 June-2 July; Addink, E.A., F.M.B., ISPRS Working Groups, Ghent, Belgium, 2010.
[2] A. A. Alesheikh, A. Ghorbanali, and A. Talebzadeh, “Generation the coastline change map for Urmia Lake by TM and ETM+ imagery,” Map Asia Conference 2004.
[3] A. Puissant, S. Lefèvre, and J. Weber 2008, “Coastline extraction in VHR imagery using mathematical morphology with spatial and spectral knowledge,” SPRS Congress Beijing 2008, China.
[4] R. Li, R. Ma, and K. Di, “Digital tide-coordinated shorelines,” Journal of Marine Geodesy, Vol. 25(1–2), pp. 27–36, 2002.
[5] T. Abdelgayoum Ali, New methods for positional quality assessment and change analysis of shoreline features, Thesis, The Ohio State University, 2003.
[6] P.S. Frazier, and K.J. Page, “Water body detection and delineation with Landsat TM data,” Photogramm. Eng. Remote Sensing, Vol. 66 (2), pp. 1461-1467, 2000.
[7] A.M. Muslim, G.M. Foody, and P.M. Atkinson, “Localized soft classification for super-resolution mapping of the shoreline,” International Journal of Remote Sensing, Vol. 27 (11), pp. 2271–2285, 2006.
[8] A. Guariglia, A. Buonamassa, A. Losurdo, R. Saladino, M. L. Trivigno, A. Zaccagnino, and A. Colangelo, “A multisource approach for coastline mapping and identification of shoreline changes,” Annals of Geophysics, Vol. 49, n. 1, February 2006.
[9] C. Parente, and R. Santamaria, “Synthetic Sensor of Landsat 7 ETM+ Imagery to Compare and Evaluate Pan-sharpening Methods”, Sensors and transducers, 177(8): 294-301. ISSN 1726-5479, 2014.
[10] P. Maglione, C. Parente, R. Santamaria, and A. Vallario, “Modelli tematici 3D della copertura del suolo a partire da DTM e immagini telerilevate ad alta risoluzione WorldView-2,” Rendiconti Online della Società Geologica Italiana, Vol. 30, 2014, pp. 33-40.

[11] B. Salehi, Y. Zhang, M. Zhong, and V. Dey, “Object-Based Classification of Urban Areas Using VHR Imagery and Height Points Ancillary Data,” Remote Sensing, Vol. 4 (8), pp. 2256-2276, 2012.
[12] W.Q. Zhou, A. Troy, and M. Grove, “Object-based land cover classification and change analysis in the Baltimore metropolitan area using multitemporal high resolution remote sensing data,” Sensors, Vol. 8 (3), 2008.
[13] A.M. Marangoz, K.S. Gormus, M. Oruc, H.S. Kutoglu, and Z. Alkis, “Verification of temporal analysis of coastline using object-based image classification derived from Landsat-5 images of Karasu, Sakarya-Turkey,” Proceedings of the 4th GEOBIA, Rio de Janeiro, Brazil, May 7-9, 2012.
[14] E. Cocco, M.A. De Magistris, and Y. Iacono, “Dinamica ed evoluzione del litorale campano-laziale: Il complesso di foce Volturno,” Atti del VI Congresso A:I.O.L., Livorno, Italia, 1984.
[15] M. Basile Giannini, P. Maglione, C. Parente, and R. Santamaria, “Cartography and remote sensing for coastal erosion analysis,” Proceedings of the Coastal Process Conference 2011, Napoli 27-29 April 2011, Coastal Processes II, Benassai, G., Brebbia, C.A., and Rodriguez, G.; WIT Press: Southampton, UK, pp. 65-76.
[16] C. Parente, R. Santamaria, “Increasing Geometric Resolution of Data Supplied by Quickbird Multispectral Sensors,” Sensors and transducers, vol. 156, Issue 9, pp. 111-115, 2013.
[17] P.A. Brivio, G. Lechi, and E. Zilioli, Principi e metodi di telerilevamento, CittàStudi Edizioni, Torino, 2006.
[18] R. P. Gupta, Remote Sensing Geology, Springer-Verlag, Berlin, Germany, 2003.
[19] S. A. Drury, Image interpretation in geology, Chapman & Hall, London, 2001.
[20] J.C. Russ, The image processing handbook, 3rd ed., CRC Press, Broken Sound Parkway NW, USA, 2011.
[21] ENVI, ENVI Zoom Software – Help, 2011.
[22] X. Yang, Urban Remote Sensing. Monitoring, Synthesis and Modeling in the Urban Environment, Wiley-Blackwell, Oxford, 2011.
[23] A. Darwish, K. Leukert, and W. Reinhart, “Image segmentation for the purpose of object-based classification,” Geoscience and Remote Sensing Symposium, Toulouse, France, 21-25 July, 2003.
[24] T. Blaschke “Object based image analysis for remote sensing,” ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 65, pp. 2-6, 2010.
[25] R.V. Platt, and L. Rapoza, “An evaluation of an object-oriented paradigm for land use/land cover classification,” Professional geographer, Vol. 60, pp. 87-100, 2008.
[26] S. W. Myint, P. Gober, A. Brazel, S. Grossman-Clarke, and Q. Weng, “Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery,” Remote Sensing of Environment, Vol. 115 (5), pp. 1145-1161, 2011.
[27] J. Xiaoying, Segmentation-based image processing system, ITT Manufacturing Enterprises Inc., Wilmington, DE (US). Report No.US 2009/0123070 A1, 2009.
[28] D.J. Robinson, N.J. Redding, and D.J. Crisp, “Implementation of a fast algorithm for segmenting SAR imagery,” DSTO Electronics and Surveillance Research Laboratory, Edinburgh, South Australia, Report No.1242, 2002.
[29] ESRI, Automation of Map Generalization - The Cutting-Edge Technology, ESRI, United States of America,1996.
[30] E. Bodansky, A. Gribov, M. Pilouk, “Smoothing and Compression of Lines Obtained by Raster-to-Vector Conversion,” Graphics Recognition Algorithms and applications, Liu, W., Llados, J., and Ogier, J., Springer, Berlin, Germany, pp. 256-265. 2002.
[31] ESRI, ArcGIS 9.3 – Help, 2008.

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