IDENTIFICATION OF URBAN FEATURES USING OBJECT-ORIENTED IMAGE ANALYSIS

O. D. Mavrantza[a] and D. P. Argialas[b]

[a] KTIMATOLOGIO S.A. (Hellenic Cadastral Agency), Messogion Ave 339, Halandri, 15231, Athens, Greece – omavratz@ktimatologio.gr

[b] Laboratory of Remote Sensing, School of Rural and Surveying Engineering, National Technical University of Athens, Greece, Heroon Polytechneiou 9, Zografos Campus, 157 80, Athens, Greece – argialas@central.ntua.gr

KEY WORDS: Remote Sensing, Buildings, Edge Extraction, DSM, Automation, Land cover, Knowledge-based System

ABSTRACT:

The objective of this work was the presentation of a knowledge-based framework for the identification of urban features, as well as additional land cover types, contained in the image scene. The test area used was located in an urban environment of Aghios Stefanos, Attica. An IKONOS image (spatial resolution of 1m-resampled) was acquired for the study area and further pre-processed. Furthermore, supplementary geo-data were created and embedded in the knowledge-based system focused on the identification of urban characteristics (e.g. building boundaries), such as derived thematic data from remote sensing techniques and the constructed DSM of the study area (with a spacing of 3m), which was extracted using photogrammetric methods, for providing the required 3-D information.

The knowledge-based methodological framework consisted of: (1) Problem conceptualization and knowledge acquisition, which involved the identification of urban features and surrounding land cover classes faced by "decoding" of knowledge based on the existing data types and context. Furthermore, remote sensing analysis methods, implementation of edge detection algorithms and multi-scale hierarchical segmentation were investigated and applied. (2) Knowledge representation, which was performed using object-oriented image classification using fuzzy representation models (proper Fuzzy Membership Functions (FMF) or Nearest Neighbor Classification (NNC)) for the assignment of objects into the defined classes.

The output result of the proposed knowledge-based identification system is expected to be a final map that contained urban features of interest (such as building boundaries and road segments) and additional land-cover classes which consist the natural scene of the study area (e.g. vegetated regions).

1. INTRODUCTION

Photointerpretation of linear information is a subjective process and therefore there is a substantial need for automation of extracting linear information using automated techniques. Certain efforts were made in this direction including the application of edge enhancement and parametric / non-parametric detection algorithms, segmentation algorithms, wavelets, variational models, active contours, neuro-fuzzy systems, Hough Transform etc.

However it is difficult to choose among optimal algorithms since the complex scenes portrayed on satellite images are strongly dependent on the radiometric and physical properties of the sensors and on the illumination properties and topographic relief of each scene. Usually, the nature of information to be extracted and its scale and context determines the "suitability" of the method applied for linear feature extraction (medium-level analysis).

Concerning high level analysis (image understanding), the identification of the extracted features consists a more complex research topic due to limitations of the designed recognition systems as well as due to the incompetence of fully "simulating" human perception in different recognition tasks. Much scientific effort has been made in the domain of image understanding, where several recognition methodologies have been proposed for serving diverse application tasks (e.g. biomedicine, understanding of natural scenes, etc). Integrated image analysis systems involving multi-scale and multi-source data segmentation, object-oriented representation, fuzzy and other types of classification have been recently involved for various applications. A similar methodology by the authors has successfully been applied for the identification of topographic and geological lineaments using coarser spatial resolution satellite data (such as LANDSAT-ETM+, with a spatial resolution of 30m) in a sedimentary, not urban, geotectonic environment (Mavrantza and Argialas, 2003, 2006).

1.1 Edge Detection Operators: Overview

In image processing and computer vision, edge detection treats the localization of significant variations of a gray level image and the identification of the physical and geometrical properties of objects of the scene. The variations in the gray level image commonly include discontinuities (step edges), local extrema (line edges) and junctions. Most recent edge detectors are autonomous and multi-scale and include three main processing steps: smoothing, differentiation and labeling. The edge detectors vary according to these processing steps, to their goals, and to their mathematical and computational complexity (Ziou and Tabbone, 1997).

In the present work, only step edge detectors were examined, which can generally be grouped into two major categories:

1. Optimal gradient-based detectors (e.g. the Canny algorithm, etc.).

2. Operators using parametric fitting models (e.g. the *EDISON* edge detector by Meer and Georgescu (2001), etc) (Ziou and Tabbone, 1997).

1.2 Urban Feature Extraction and Mapping: Overview

Concerning the automatic approach in urban feature extraction (specifically, roads and building boundaries), several categories of processes were applied including:

1. Diverse wavelet analysis methods such as edge detection based on scale multiplication (Zang and Bao, 2002), contourlet transform (Do and Vetterli, 2005), etc.
2. Snakes (Agouris *et.al.*, 2001), Variational models, geodesic active contours (Mumford and Shah, 1989, Karantzalos, et.al., 2007).
3. Optimal edge detection algorithms (Heath et.al., 1997).
4. Object oriented image analysis for the identification of informal settlements (Hoffman, 2001).

1.3 Motivation and aim

From the thorough examination of the literature (as it was also presented in Section 1.2), it is inferred that computer-assisted methods for the extraction of urban features such as building boundaries and road segments were mostly based on the spectral and textural characteristics of these features.

Despite of the good spatial accuracy most of the aforementioned methods provide, redundant non-urban features with similar spectral characteristics were also extracted. In such cases, additional post-processing approaches are required for the discrimination of the urban and the non-urban features (Argialas, et.al, 2007).

On the other hand, optimal edge detectors (e.g. the Canny algorithm) have already been successfully applied on multi-scale natural scenes with quite satisfactory results (binary images with one-pixel thickness, efficient length, pixel connectivity and very good spatial (even sub-pixel) accuracy) (Heath et.al., 1997, Mavrantza and Argialas, 2007). The integration of optimal edge detection techniques and a knowledge-based approach would quite sufficiently combine the textural and spectral information of all the intrinsic features of a natural scene portrayed in a satellite image with the spatial and contextual information of their adjacent features for the discrimination of their semantic content. That means the discrimination of urban and non-urban features can be achieved by exploiting the semantic information of the participating features.

The integration of optimal edge detection techniques and a knowledge-based approach has already been investigated by the authors for the extraction and identification of topographic and geologic lineaments with quite successful results (Mavrantza and Argialas, 2006).

2. METHODOLOGY AND RESULTS

2.1 Study area and data used

In the present study, an IKONOS very high resolution (VHR) image of the extended area of Attica Prefecture (Aghios Stefanos area), with a spatial resolution of 1m-resampled and acquired in year 2000 (Figure 1), as well as the Digital Surface Model of the same area with 3m spacing were used as initial input geo-data.

In Figure 1, the pseudocolor composite RGB-421 of the IKONOS VHR multispectral image with spatial resolution of 1m-resampled and size 934x1070 pixels is presented. Man-made features appear with hues of blue, while vegetated areas appear with different hues of red due to the vegetation reflectance in the infrared band.

Figure 1: Pseudocolor composite RGB-421 of the IKONOS VHR image with spatial resolution of 1m-resampled and size 934x1070 pixels.

2.2 Image pre-processing

In the pre-processing stage, the IKONOS of the study area was geodetically transformed into the Transverse Mercator Projection and the Hellenic Geodetic Datum (HGRS87). The positional accuracy of the georectified image was approximately from 1.5-3.0 meters.

For the implementation of the Pratt evaluation metric (which is in detail described in a following section), an ancillary ground truth (reference) file was required as input. This ground truth file was developed containing all the visually interpreted linear segments related to building boundaries as well as road segments, from the IKONOS image (and verified on the ground), represented with their X, Y coordinates and the total number of the actual edge points (in an ASCII format file).

2.3 Framework for the design of the knowledge-based system

The present work is a generalized framework of the design of a knowledge–based system for the automated extraction and identification of urban / peri-urban features and additional land cover types of the natural scene (Figure 2).

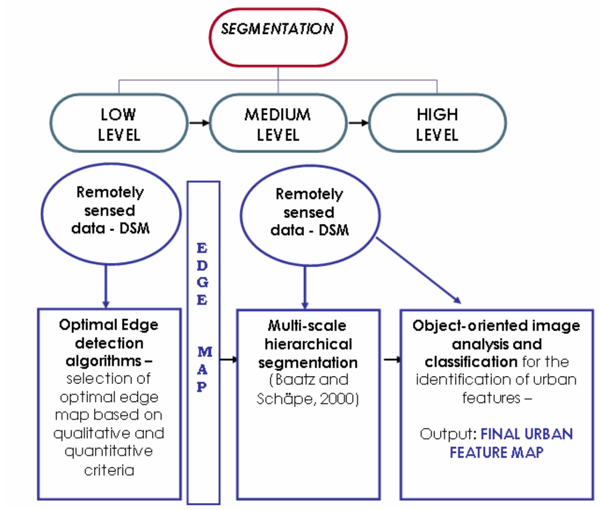

Figure 2: General methodological framework for the extraction and identification of urban features (Mavrantza and Argialas, 2007).

The knowledge-based framework consisted of the following methodological stages:

1. Problem conceptualization and knowledge acquisition: At this stage, the identification of urban features and surrounding land cover classes was faced by covering aspects like (a) the determination of the type of acquired and created geo-data in order to assist to the derivation of the information of interest, (b) the categories of expected land cover to be identified, (c) the sources of information to be required for feature identification (e.g. photointerpretative (qualitative) knowledge). In addition, "decoding" of knowledge was performed based on the existing data types and context. Furthermore, low- and medium level image analysis was performed in order to obtain the required geo-data for being introduced to the knowledge-based identification system. Low-level image analysis techniques contained (a) *Remote sensing analysis methods* and (b) *Edge detection algorithms*. The implementation of optimal edge detection algorithms (e.g. the Canny algorithm, the *EDISON* algorithm, etc) as well as their qualitative / quantitative assessment, were performed for the creation of the "optimal edge maps", which contained the highest amount of information of interest and at the same time shall keep the false-positive (redundant edges) at the minimum level. These output edge maps were further introduced into the knowledge-based system for being "transformed" into the final thematic (urban feature) map containing the identified features of interest. Finally, medium level image analysis contained multi-scale hierarchical segmentation (Baatz and Schäpe, 1999) was also performed in order to create object segments to be assigned into semantic land-cover classes in the knowledge-based system.

2. Knowledge representation: At this stage, knowledge representation was performed using object-oriented image classification using fuzzy representation. The inherent land cover classes / subclasses were determined at each level of hierarchy according to the type and information content of geodata used. The determination of the proper class / sub-class attributes was based on the following intrinsic image properties: *spectral, geometric, spatial relation and context*. These attributes followed the "general-to-specific" inheritance principle. In addition, the class attributes were connected with *AND / OR / MEAN* logical operators according to each weight criterion for the further assignment of objects to the corresponding classes. The appropriate fuzzy classification model (proper Fuzzy Membership Functions (FMF) or Nearest Neighbor Classification (NNC)) for the assignment of objects into the defined classes was also determined.

2.4 Remote Sensing Methodology

During the stage of problem conceptualization and knowledge acquisition, Remote Sensing methods and techniques were applied for the derivation of useful spectral information concerning the land cover types inherent in the satellite images. These methods included RGB colour composition (Figure 1), PCA analysis, ISODATA unsupervised clustering (Figure 3), decorrelation stretching (Figure 4), as well as texture analysis (textural metrics by Haralick). Appropriate thematic maps derived from this stage were introduced into the knowledge-based system for assisting the discrimination of land cover types and the urban features of interest.

Indicatively, selected thematic maps derived from remote sensing techniques are presented in Figures 3 and 4. These thematic maps were used as input to the knowledge-based system for the identification and discrimination of the land cover classes portrayed in the IKONOS image by exploiting their spectral attributes.

In Figure 3 the thematic map using ISODATA unsupervised clustering of the IKONOS image is presented. Urban features (e.g. roads, squares, parking lots) are illustrated with gray colour. Green areas are presented with hues of green. Buildings or building facilities are depicted with beige and lilac colour. The ISODATA classification map was introduced to the knowledge-based system in order to provide information about the spectral attributes and the spatial context of the land cover classes of the image.

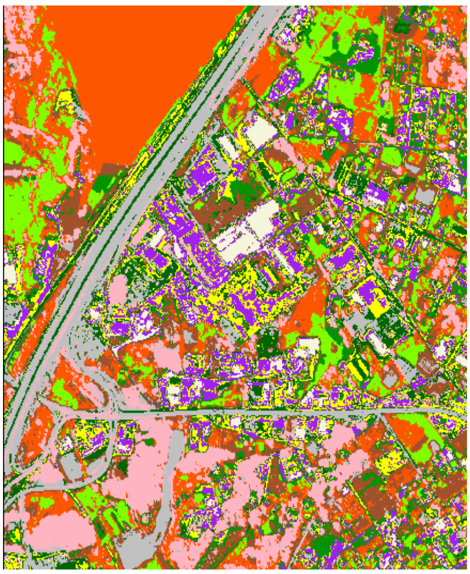

Figure 3: Thematic map using ISODATA unsupervised clustering of the IKONOS image.

In Figure 4, the RGB-421 colour composite derived by decorrelation stretching of the IKONOS image bands is presented. Urban features (e.g. roads, squares, parking lots) are illustrated with bluish-green colour.

Figure 4: RGB-421 colour composite derived by decorrelation stretching of the IKONOS image bands.

2.5 Optimal edge detection algorithms: Implementation

On the band 4 of the IKONOS very high resolution image for the study area of Aghios Stefanos, Attica, the following edge detectors were selected, applied and assessed (Mavrantza and Argialas, 2007):

(a) The Canny edge detection algorithm (Canny, 1986)
(b) The Rothwell algorithm (Rothwell *et.al.*, 1994)
(c) The *LOG-LIN* algorithm (Iverson and Zucker, 1995)
(d) The *SUSAN* operator (Smith and Brady, 1997)
(e) The anisotropic diffusion algorithm of Black (Black, *et.al.*, 1998)
(f) The Bezdek algorithm (Bezdek, *et.al.*, 1998), and
(g) The *EDISON* algorithm (Meer and Georgescu, 2001)

For each algorithm, the combinations of input parameter sets were selected based on trial-and-error experiments and assessed (a) using the performance evaluation measures of *Pratt* and *Rosenfeld* (Abdou and Pratt, 1979, Kitchen and Rosenfeld, 1981) (Table 1) and (b) by evaluating the optical correspondence to the ground map data for ensuring the "interpretability" of the output edge image.

ALGORITHMS	***ROSENFELD* METRICS IKONOS - band 4**	***PRATT* METRICS IKONOS - band 4**
CANNY	0,6697	0,5290
ROTHWELL	0,6915	0,4811
BLACK	0,6470	0,4530
SUSAN	0,7536	0,5785
IVERSON	0,6372	0,5984
BEZDEK	0,7708	0,4989
EDISON	0,6695	0,5340

Table 1: Performance evaluation metrics (Rosenfeld and Pratt) for the band 4 of the IKONOS satellite image of the study area of Aghios Stefanos

From the stage of the edge detection implementation, the output edge map of the *EDISON* algorithm was selected as the "best" because it fulfils the criteria of (a) good edge extraction (good edge localization, edge connectivity and edge response) and (b) sufficient interpretation ability of the semantic content (according to the qualitative (visual) and quantitative (measurement) criteria set). On the other hand, the output edge map of the application of the Bezdek algorithm was the optimum in terms of visual "interpretabity" and good appearance of semantic information (e.g. building boundaries), but needs further post-processing for achieving sufficient edge connectivity and coherence and edge thickness. These two output maps were inserted into the knowledge-based system in order to be segmented and classified for the production of the final urban feature thematic map (Mavrantza and Argialas, 2007).

Using the *EDISON* algorithm, the best output edge map was derived using the following combination of parameters: a) Gradient=4.00, b) Minimum length=7.00, (c)–(e) Non-maxima suppression: Type = line, Rank=0.5 and Confidence=0.5, (f)–(h) T_{high} Hysteresis: Type = line, Rank==0.95 and Confidence =0.98, and (i)-(k) T_{low} Hysteresis: Type = line, Rank =0.99 and Confidence =0.96 (Figure 5 – left image). Using the Bezdek algorithm, the best output edge map was derived using the following input parameter values: *Tau*=2.00 and *Binary_Threshold*=60.00 (Figure 5 – right image)

Figure 5: **Left**: The *EDISON* output edge map. Indicatively, an area with buildings is delineated with a red ellipse. **Right**: The Bezdek output edge map. The same area as in the left image is delineated with a red ellipse on the right image.

2.6 Multi-scale hierarchical segmentation

Multi-resolution hierarchical segmentation proposed by Baatz and Schäpe (1999) and object-oriented image analysis were performed in the environment of the *eCognition* object-oriented image analysis software by Definiens. During this procedure, the input data were segmented into raster primitive regions, which were next assigned into defined thematic land cover classes. The hierarchical segmentation of the input geo-data was performed using five (5) segmentation levels in pre-defined order, data membership factor and selected segmentation parameters, so that the physical boundaries of the object classes of upper and lower levels of segmentation hierarchy won't be affected. In Table 2, detailed information is presented about the input geo-data into the knowledge-based system, their type, the segmentation parameters used as well as the performed segmentation order.

GEODATA TYPE	MULTI-SCALE HIERARCHICAL SEGMENTATION PARAMETERS					FINAL SEGMENTATION LEVEL (Levels 1-5)	SEGMENTATION ORDER (Levels 1-5)
	Scale Parameter	Color Criterion	Shape Criterion	Shape Criterion			
				Compactness	Smoothness		
BEZDEK (membership factor MF=1.0) and EDISON (membership factor 0.5) edge detection maps	10	0.7	0.3	0.5	0.5	5 (upper)	1
Thematic maps of decorrelation stretch (MF=1.0), PCA (MF=1.0), IKONOS (4 bands) (MF=1.0), BEZDEK (membership factor MF=1.0) and EDISON (membership factor 0.5)	6	0.7	0.3	0.4	0.6	4	2
ISODATA map and IKONOS (4 bands) (MF=1.0)	3	0.9	0.1	0.2	0.8	3	3
DSM and IKONOS (4 bands) (MF=1.0)	7	0.6	0.4	0.4	0.6	2	4
EDISON edge detection map (membership factor 1.0)	10	0.7	0.3	0.5	0.5	1 (lower)	5

Table 2: Geo-data type, multi-scale segmentation parameters and performed segmentation order during the segmentation process.

2.7 Knowledge-based identification system of urban features

The knowledge-based identification of the urban and the non-urban features was based on the construction of an object-oriented knowledge base of the inherent land cover classes and the classification (assignment) of the primitive objects derived at the segmentation stage into these semantic classes. A theoretical approach preceded the object-oriented classification process concerning *(a)* the determination of the proper classes / sub-classes of every segmentation level of hierarchy, *(b)* the determination of the class attributes based on the spectral, spatial and contextual characteristics of these classes, *(c)* the determination of the proper fuzzy representation method (Fuzzy Membership Function values or NNC) and finally, *(d)* the proper classification order at each level of hierarchy which also determines the construction of the fuzzy classification rules.

In Figure 6, the class hierarchy is presented, which was used for the object-oriented identification of the inherent land cover classes (urban and non-urban feature classes).

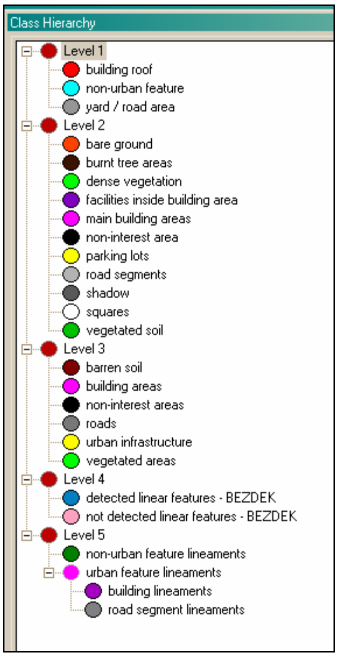

Figure 6: The Class hierarchy used for the object-oriented identification of the inherent land cover classes (urban and non-urban feature classes).

Due to paper length limitation, a fuzzy classification rule (combination of those attributes that determine a class / sub-class) is indicatively presented in Figure 7, while in Figure 8 the corresponding Fuzzy Membership Function of a selected attribute is presented.

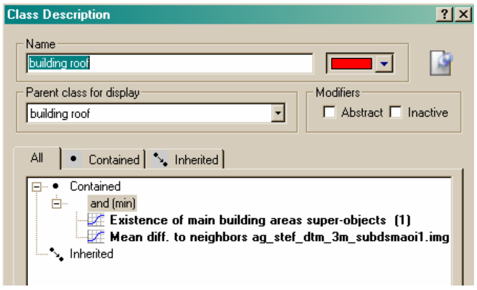

Figure 7: The attribute set of the definition of class **building roof** – Level 1

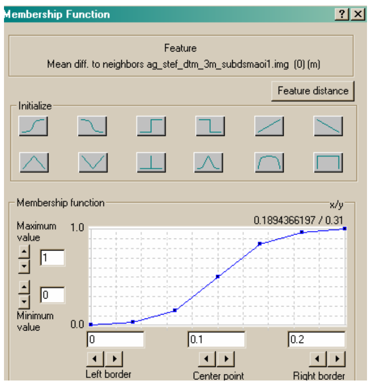

Figure 8: Fuzzy Membership Function for the attribute **Mean diff. To neighbors ag_stef_dsm_subdsmaoi1.img**.

3. DISCUSSION AND CONCLUSIONS

The presented methodological framework was used for the identification of urban features, as well as additional land cover types, contained in the geo-data used. One main aspect from the application of optimal edge detection algorithms was their good performance in terms of coherence, edge localization and high edge response, and therefore they generally provide useful tools towards automated urban / peri-urban mapping by yielding into “interpretable” edge maps. Furthermore, edge maps derived by optimal edge detection can generally be introduced into a knowledge-based system to provide final urban feature thematic maps of useful semantic information, while “isolating” the redundant information of non-interest (non-urban features). The output result of the proposed knowledge-based identification system is expected to be a final map that contains urban features of interest (such as building boundaries and road segments) and additional land-cover classes which consisted the natural scene of the study area (e.g. vegetated regions).

4. REFERENCES

Abdou, I. E. and W. K. Pratt, 1979. Quantitative Design and Evaluation of Enhancement / Thresholding Edge Detectors. *Proceedings of IEEE*, 67, pp. 753-763.

Agouris, P., A. Stefanidis and S. Gyftakis, 2001. Differential snakes for change detection in road segments. *Photogrammetric Engineering and Remote Sensing,* 67, pp. 1391-1399.

Argialas, D., A. Georgopoulos, D. Rokos, Ch. Ioannidis, N. Alvertos, N. Paragios, E. Papadaki, P. Kolokoussis, Ch. Iossifidis, O. Mavrantza, Ch. Papasaika, V. Noutsou, A. Tzotsos, P. Deltsidis, P. Michalis and K. Karantzalos, 2007. Development of advanced Remote Sensing and Photogrammetry Techniques for the implementation of urban geospatial databases, In ***Pythagoras:*** *Conference for the Scientific Research at the National Technical University of Athens*, 5-8 July, Plomari, Lesvos

Baatz, M. and A. Schäpe, 1999. Multiresolution segmentation – an optimization approach for high quality multi-scale image segmentation. In Strobl, Blaschke and Greisebener (Ed.): *Angewandte Geographische Informationsverarbeitung, XI. Beiträge zum AGIT-Symposium*, Salzburg, Karlsruhe, Herbert Wichmann Verlag.

Bezdek, J. C., R. Chandrasekhan and Y. Attikiouzel, 1998. A geometric approach to edge detection. *IEEE Transactions. on Fuzzy Systems,* 6, pp. 52-75.

Black, M., G. Sapiro, D. Marimont and D. Heeger, 1998. Robust Anisotropic Diffusion. *IEEE Transactions on Image Processing*, 7, pp. 421-432.

Canny, J. F., 1986. A computational approach to edge detection. *IEEE Transactions. on Pattern Analysis and Machine Intelligence*, 8, pp. 679-714.

Heath, M., S. Sarkar, T. Sanocki and K. Bowyer, 1997. A robust visual method for assessing the relative performance of edge detection algorithms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol.-PAMI-19, pp. 1338-1359.

Hofmann, P., 2001. Detecting Informal Settlements from IKONOS Image Data Using Methods of Object Oriented Image Analysis – An Example from Cape Town (South Africa). In: *Jürgens, C. (Ed.): Remote Sensing of Urban Areas / Fernerkundung in urbanen Räumen*. Regensburg: University Regensburg, Germany, pp. 41-42.

Iverson, L. A. and S. W. Zucker, 1995. Logical / linear operators for image curves. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17, pp. 982-996.

Kitchen, L. and A. Rosenfeld, 1981. Edge Evaluation using Local Edge Coherence. *IEEE Transactions on Systems, Man and Cybernetics*, 11, pp. 597-605.

Mavrantza, O. D. and D. P. Argialas, 2007. Edge Detection Techniques For Extracting Linear Information In An Urban / Peri-Urban Environment”, *Proceedings of the FIG Commission 3 Workshop “Spatial Information Management toward Legalizing Informal Urban Development”,* 28-31 March, Athens, Greece, 15 p.

Mavrantza, O. D. and D. P Argialas, 2006. Object-oriented image analysis for the identification of geologic lineaments. *Proceedings of the 1st International Conference on Object-based Image Analysis (OBIA): Automated classification, mapping and updating techniques - Geology, soil, natural resources,* 5-7 July, Salzburg, Austria, 7p, http://www.commission4.isprs.org/obia06/papers.htm.

Mavrantza, O. D. and D. P. Argialas, 2003. Implementation and evaluation of spatial filtering and edge detection techniques for lineament mapping - Case study: Alevrada, Central Greece. *Proceedings of SPIE International Conference on Remote Sensing: Remote Sensing for Environmental Monitoring, GIS Applications, and Geology II,* M. Ehlers (editor), *SPIE*-4886, pp. 417-428, SPIE Press, Bellingham, WA.

Meer, P. and B. Georgescu, 2001. Edge detection with embedded confidence. *IEEE Transactions on Pattern Analysis and Machine Intelligence.*, PAMI-23, pp. 1351-1365.

Rothwell, Ch., J. Mundy, B. Hoffman and V. Nguyen, 1994. Driving Vision by Topology. TR-2444 – Programme 4, INRIA, pp. 1-29.

Smith, S. M. and J. M. Brady, 1997. SUSAN-A New Approach to Low Level Image Processing. *International Journal of Computer Vision*, 23(1), pp. 45-78.

Ziou, D. and S. Tabbone, 1997. Edge Detection Techniques – An Overview. ***TR-195,*** Département de Math et Informatique, Université de Sherbrooke, Québec, Canada, pp. 1-41.

ACKNOWLEDGEMENTS

This work was based on data (IKONOS image) and methodology fully conducted under the “EPEAEK-PYTHAGORAS-II” Research Program - National Technical University of Athens, Greece. The ”PYTHAGORAS-II” Project is a part of the Operational Program for Educational and Vocational Training II (EPEAEK-II) , which is co-funded by the European Social Fund (75%) and National Resources (25%).