The Role of Edge Detection Techniques for the Extraction of Linear Information in Urban / Peri-Urban Environment

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Summary
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 detection operators, wavelets, 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.
Therefore, the category of information to be extracted (scale and context) determines the "suitability" of the method applied for linear feature extraction. In this context, the objective of this work was the implementation, evaluation and comparison of selected optimal edge detection algorithms combined with complementary remote sensing methods towards automated linear feature extraction (roads, land use boundaries, buildings, etc) in an urban / peri-urban environment. The test areas used were located in the extended area Attica Prefecture. A multispectral IKONOS image and panchromatic KVR-1000 imagery of two different dates were acquired for the case studies of Aghios Stefanos and Penteli, Attica, Greece respectively and processed by the following edge detectors: (a) The Canny edge detection algorithm, (b) The Rothwell algorithm, (c) The LOG-LIN algorithm, (d) The SUSAN operator, (e) The anisotropic diffusion algorithm of Black, (f) The Bezdek algorithm and (g) The EDISON algorithm.
The resulted edge maps were then compared to thematic maps resulted by applied remote sensing methods and techniques and assessed using statistical methodology. Finally, the performance and behavior of each algorithm for urban feature extraction was assessed as well as the sufficiency of the edge detection methodology for environmental change detection purposes.

1. INTRODUCTION

The urban and peri-urban environment is a widely investigated research topic among geo-scientists, as well as a very crucial subject for enforcing administrative and legal policies. Nowadays, new geo-data resources from high spatial resolution remote sensing sensors (e.g. IKONOS, Quickbird, KVR, etc) have the potential to improve mapping and analysis of urban land cover / land use structures and to monitor related dynamics. Remote Sensing methodology can provide very powerful tools and means for monitoring the change dynamics of the urban environment by exploiting the spectral and spatial information and context of these geo-data and for further decision-making.

For many years, edge detection has been proved a very valuable tool for automating the extraction of information at a low level. The aim of edge detection is to extract features, as meaningful as possible depending on the physical illumination properties of an image. Edge detection techniques have been successfully applied in the domains of Computer Vision (Haralick, 1984, Canny, 1986, etc), Biomedicine (Bezdek, et.al., 1998), Geomorphology (Argialas and Mavrantza, 2004), etc.

In this work, the application and performance of sophisticated and automated edge detection techniques is assessed using spectral and spatial information from high resolution images in an urban / peri-urban environment, as a standalone methodology and as a combined methodology with other remote sensing methods and techniques for extracting urban features of interest (building boundaries, road segments, etc).

1.1 Edge detection algorithms: An 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 detection algorithms vary according to these processing steps, to their goals, and to their mathematical and computational complexity (Ziou and Tabbone, 1997).

Furthermore, contextual detectors have also been designed and implemented for the extraction of edges. Nevertheless, they are based on knowledge used to perform edge extraction and are considered as task-dependent. Similarly edge detection approaches are also based on snakes (Agouris *et.al.*, 2001), statistical tools, and neural networks, but these approaches are not presented here.

1.2 Motivation and aim

From the thorough examination of the literature it is inferred that optimal edge detectors (e.g. the Canny algorithm) have already been successfully applied on natural scenes with quite satisfactory results (binary images with one-pixel thickness, efficient length and pixel connectivity), but have not been investigated on the context of an urban / peri-urban environment.

Many remote sensing methods have been proposed in the literature for processing single-band and multi-band images, such as vector analysis, ICA mixture models, Support Vector Machines (SVMs), Markov Random Field (MRF) Models, band differencing, cross-correlation analysis, object-oriented analysis, etc (Civco, 2002). Nevertheless, for change detection purposes the implementation and assessment of novel edge detection algorithms has never been combined to the results of remote sensing methods and techniques for change detection purposes, something that characterizes the present study.

The main aim of this study was the investigation and implementation of optimal edge detectors on the context of an urban / peri-urban environment, and its evaluation by comparison to an interpreted output map. In a subsequent effort, the produced edge maps will be introduced into a knowledge-based image analysis system for the identification of different thematic levels of information (e.g. urban areas, buildings, other land cover classes of interest) using additional thematic information layers (e.g. DSM, classification maps, supplementary thematic maps derived by remote sensing (e.g. maps from spectral indices, PCA, etc).

2. METHODOLOGY

The present research consists the first stage in the framework of the design of a knowledge–based system for the automated extraction and identification of urban / peri-urban features (Figure 1). The first stage methodology aims to the selection of the "optimal" edge maps to be introduced into the identification system for the derivation of the final urban thematic map.

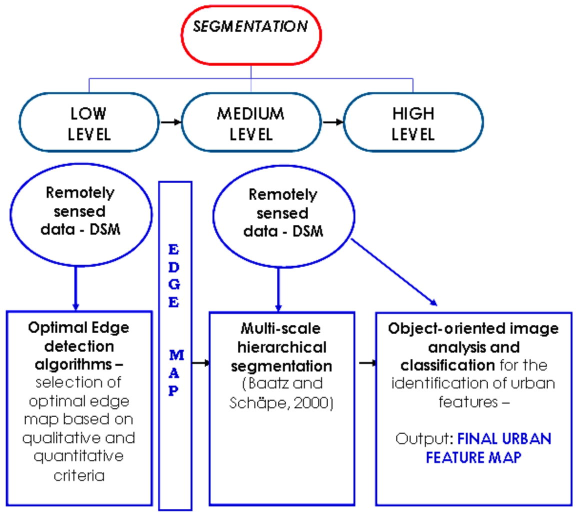

Figure 1: *General methodological framework for the extraction and identification of urban features.*

2.1 STUDY AREA AND DATA USED

In the present study, different high resolution images were used, namely 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 (Figures 2 and 3) and a panchromatic KVR-1000, very high resolution imagery (spatial resolution of 1.5m) of the Penteli area for two dates of 1998 and 1992

The main purpose for using the IKONOS image was the evaluation and comparison of selected optimal edge detection algorithms in a "pure" urban / peri-urban environment, whereas the use of KVR-1000 images intended to accentuate the suitability of optimal edge detection methodology for environmental change detection purposes in a mixed (urban / peri-urban and forested) environment.

Additionally, for the processing of KVR-1000 imagery, a supplementary vector layer containing forested areas and forests was used, which was derived from the interpretation of aerial ortho-rectified images of 1937 and the compilation with the information included in the maps of the Approved City Plan of Athens, valid since 1985 (APERTURE 2000, Karathanassi *et.al.* 2003). .

Figure 2: *Pseudocolor composite RGB-421 of the IKONOS VHR multispectral image with spatial resolution of 1m-resampled and size 421x497 pixels. 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*

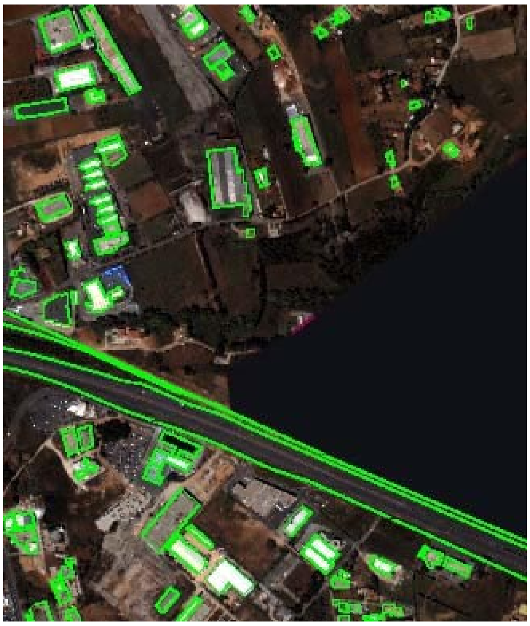

Figure 3: *Thematic overlay of photo-interpreted and ground-verified building boundaries and road segments on the image of Figure 1. This overlay was used for the visual assessment of the output edge maps.*

2.2 Image pre-processing

In the pre-processing stage, an IKONOS and two KVR-1000 images were geodetically transformed into the Transverse Mercator Projection and the Hellenic Geodetic Datum (HGRS87). The positional accuracy of the images was approximately from 1.5-3.0 meters for both images.

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 Edge detection algorithms: Implementation and evaluation

2.3.1 Case study: IKONOS multispectral image – Aghios Stefanos area, Attica

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:

(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 mostly the performance evaluation measures of Pratt and Rosenfeld (Abdou and Pratt, 1979; Kitchen and Rosenfeld, 1981) (which will be explained below), and (b) by evaluating the optical correspondence to the ground map (Figure 3) for ensuring the “interpretability” of the output edge image. In this paper, the best results (qualitatively and quantitatively) of each edge detection algorithm are presented.

Concerning the selection of the input parameters to the edge detection algorithms, the theoretical range of input parameter values were formed based on the initial values given by the authors (algorithm designers), and were indicative for cases of edge detection on aerial images. The range of values used in this work is presented in Table 1 (Sarkar, *et.al.*, 2001).

Table 1: *Experimental value range of input parameters for the implementation and assessment of the selected edge detection algorithms.*

ALGORITHM	METHOD DESCRIPTION	VALUE RANGE OF INPUT PARAMETERS		
		I	II	III
Canny	First derivative of Gaussian function, non-maxima suppression, hysteresis thresholding	***Standard deviation σ =0.2 - 2.0***	*Low hysteresis Threshold T_{low} = 0.2 - 0.6*	*High hysteresis Threshold T_{high} = 0.5 – 0.9*
Rothwell	Canny with topology added	***Standard deviation σ =0.5 - 2.0***	*T_{low} = 3.0 – 11.0*	*Dynamic thresholdin g parameter alpha = 0.8 - 0.9*
***LOG-LIN* (Iverson-Zucker)**	Combination of Logical / Linear operators	***Threshold T = 0.010 – 0.025***	*16 directions of detection*	*64 degrees of freedom*
***EDISON* (Meer-Georgescu)**	Modified Canny with added measure of confidence and use of templates	*a) edge gradient=2.0 – 3.0, b) minimum edge length=3.0 - 6.0 c) – e) Non-maxima suppression: Type = line / arc, Rank=0.5 – 0.6, Confidence=0.5 - 0.8 f) – h) T_{high} for hysteresis: Type = box / arc, Rank =0.93-0.96, Confidence =0.94 - 0.98 i) – k) T_{low} for hysteresis: Type = box / arc, Rank =0.92 – 0.95, Confidence =0.92 -0.99*		
Black	Robust anisotropic diffusion	*Standard deviation σ =0.4 - 3.0*	*Standard deviation σ =0.4 - 3.0*	----
***SUSAN* (Smith-Brady)**	Isotropic (circular) detection filter (*U*nivalue *S*egment *A*ssimilating *N*ucleus - *USAN*)	*Threshold T = 20.0 - 45.0*	*Threshold T = 20.0 - 45.0*	----
Bezdek	Sobel with Takagi-Sugeno geometric fuzzy model	*Steepness Function parameterTau = 1.0 – 4.0*	*Steepness Function parameterTau = 1.0 – 4.0*	----

In the following figures, the output edge images are presented as derived from the application of the selected edge detection algorithms of Canny (Figure 4), of Rothwell (Figure 5) and of the *LOG-LIN* algorithm (Figure 6). The algorithm of Canny was applied on band 4 (near-infrared) with input parameters σ=0.6 (standard deviation for the Gaussian function), T_{low}=0.50 και T_{high}=0.90 (these are the low and the high threshold values for the performance of hysteresis thresholding). For the same region, the algorithm of Rothwell was applied using the following parameter values: σ=2.00, T_{low}=8.00 και a=0.90. The input parameter values for the *LOG-LIN* algorithm by Iverson and Zucker were T=0.040 (threshold), 16 directions and 64 degrees of freedom for the ”edge (E)” mode.

In Figure 4, **areas containing building boundaries** are illustrated with **green ellipses**. The application of the algorithm of Canny extracted edges with edges visually compatible to the **”true” building boundaries**, as presented in Figure 3. Indeed, the Canny algorithm did not detect junction edges (such as ”L”, ”Y” and ”T” edges), but it performed sufficiently in terms of ”high amount of extracted edges of interest”, especially for edges at areas of high contrast.

In Figure 5, the output edge map of the Rothwell algorithm is presented. With a **red ellipse** an extracted **junction edge** is depicted, which was not apparent in the Canny output image. The Rothwell output image (Figure 5) provides poor ”interpretability” (as far as the identification of the semantic content is concerned, but on the other hand, edges with high connectivity, coherence and sufficient edge length were extracted.

In Figure 6 the output image from the Iverson-Zucker is presented. The performance of the algorithm was sufficient in terms of ”image interpretability”, because the concept of the algorithm is based on the topological and structural features of the image.

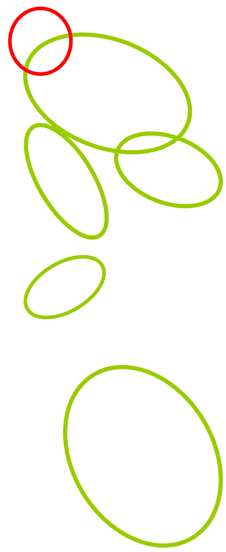

Figure 4: *Output edge map from the application of the Canny algorithm – study area of Aghios Stefanos* (IKONOS – band 4).

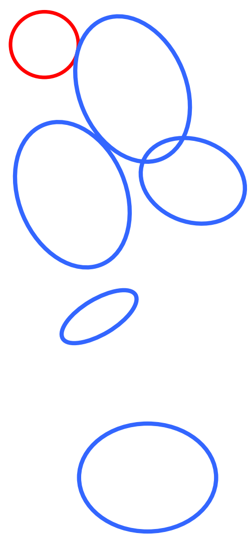

Figure 5: *Output edge map from the application of the Rothwell algorithm – study area of Aghios Stefanos* (IKONOS – band 4).

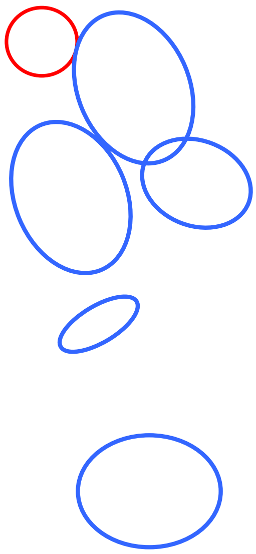

Figure 6: *Output edge map from the application of the LOG-LIN algorithm – study area of Aghios Stefanos* (IKONOS – band 4).

Concerning the performance of the anisotropic diffusion algorithm by Black et.al. (Figure 7), the combination of anisotropic diffusion with the procedures of non-maxima suppression and hysteresis thresholding allows the satisfaction of Canny's criteria for single edge response, edge coherence. Furthermore, Black's algorithm proposes a new "edge-stopping" function based on *Tukey's biweight* robust error norm, which improves the automatic stopping of the diffusion and therefore, preserves sharper boundaries, as also noted in Figure 6. In Figure 8, the output edge image from the application of the *SUSAN* algorithm on IKONOS – band 4 for *T*=50, is presented. In this output image, redundant information was extracted which deteriorates the "interpretability" of the image relative to its semantic content (e.g. difficulty in visual interpretation of building boundaries).

In Figure 9 the output edge image from the application of the *EDISON* algorithm is presented using the following input parameters: (a) Gradient = 4.00, (b) Minimum edge length=7.00, (c)–(e) Non-maxima suppression: <u>Type</u> = line, <u>Rank</u>=0.5 and <u>Confidence</u>=0.5, (f)–(h) T_{high} Hysteresis: <u>Type</u> = line, <u>Rank</u>==0.95 and <u>Confidence</u> =0.97, and (i)-(k) T_{low} Hysteresis: <u>Type</u> = line, <u>Rank</u> =0.99 and <u>Confidence</u> =0.95. Finally, in Figure 10, the output edge image from the application of the Bezdek algorithm for the same study area is presented using *Tau*=2.00 and *Binary_Threshold*=60.00 as input parameter values.

As noted in Figure 9 from the performance of the *EDISON* algorithm, additional junction edges (as presented in Figure 5 with a red ellipse) were extracted due to the embedding of the confidence measure into this modified version of the Canny algorithm, which controls the procedures of non-maxima suppression and hysteresis thresholding during the edge extraction.

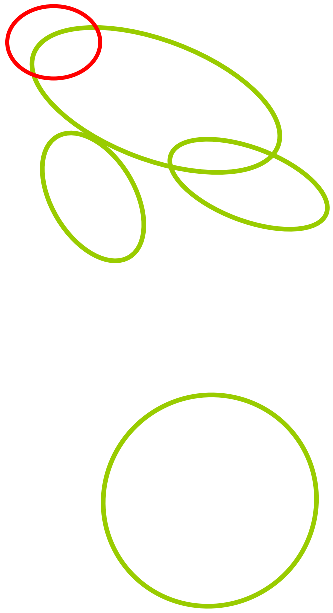

Figure 7: *Output edge map from the application of the Black algorithm – study area of Aghios Stefanos* (IKONOS – band 4) for σ=2.5.

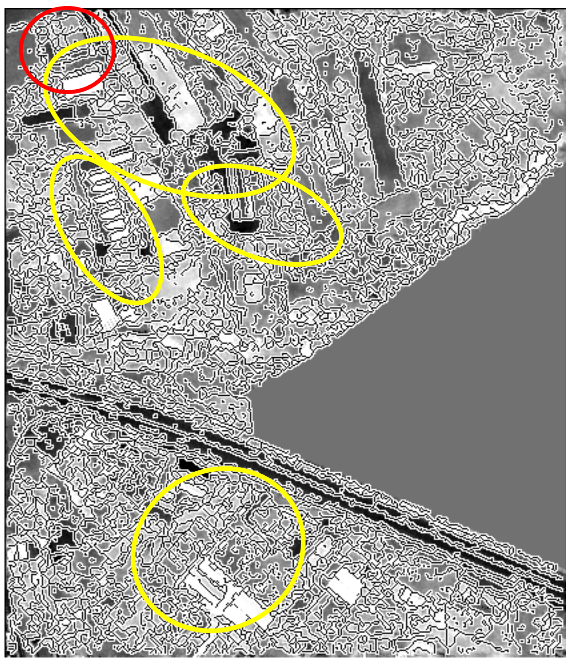

Figure 8: *Output edge map from the application of the SUSAN algorithm στην – study area of Aghios Stefanos* (IKONOS – band 4) for T=50.

Finally, the Bezdek algorithm (Figure 10) performed quite sufficiently for the extraction of meaningful edges. Since, it was based on a modification of the Sobel operator, it means that the algorithm does not ensure the extraction of single-pixel thick edges, which leads to the necessity of following thresholding procedures.

After the qualitative (visual) assessment of the edge detection output images, followed quantitative evaluation and assessment of the employed edge detection algorithms with two evaluation metrics, namely: **(1)**

The *Rosenfeld* evaluation metric (E1), which is based on the local edge coherence and measures how well an edge fits to the local neighborhood of edge pixels but it does not concern itself with the actual position of the edge, therefore it is a supplement to Pratt's evaluation metric (Parker, 1997), and **(2)**

The *Pratt* evaluation metric (E2), which is a formulated function of the distance between correct and measured edge positions, but it is also indirectly related to the false positive and false negative edges.

Pratt's metric is considered to be a performance evaluation measure that requires ground-truth files. Therefore, it is directly related to the actual position of the edge pixels and serves as a more objective quantitative evaluation measure (Parker, 1997).

In the following table (Table 2), the resulted values from the performance evaluation metrics are presented using the selected edge detection algorithms on the band 4 of the IKONOS VHR image.

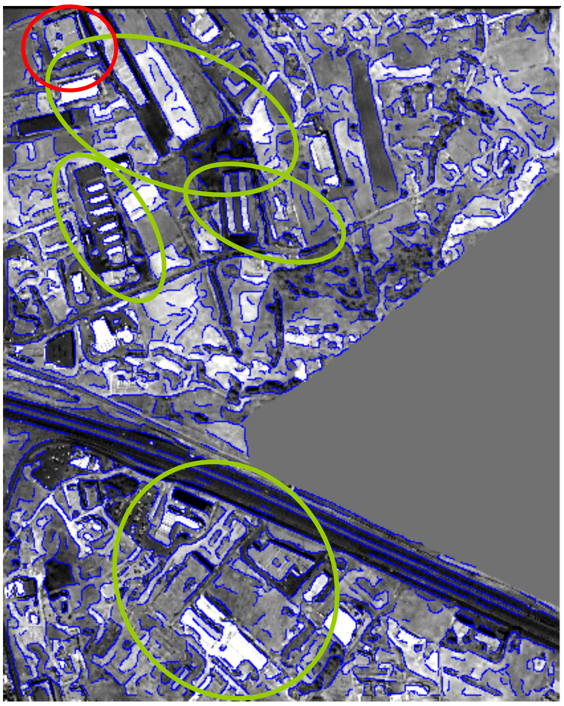

Figure 9: *Output edge map from the application of the EDISON algorithm – study area of Aghios Stefanos (IKONOS – band 4) for (a) Gradient = 4.00, (b) Minimum edge length=7.00, (c)–(e) Non-maxima suppression: Type = line, Rank=0.5 and Confidence=0.5, (f)–(h) T_{high} Hysteresis: Type = line, Rank==0.95 and Confidence =0.97, and (i)-(k) T_{low} Hysteresis: Type = line, Rank =0.99 and Confidence =0.95.*

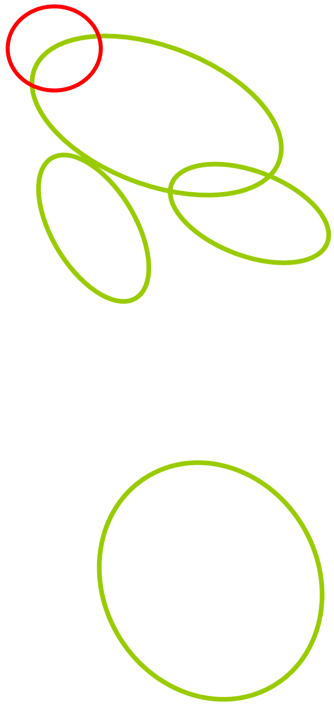

Figure 10: *Output edge map from the application of the Bezdek algorithm – study area of Aghios Stefanos (IKONOS – band 4) for Tau=2.00 and Bin_Thres=60 (DN value between 0-255).*

Table 2: *Resulted values of performance evaluation metrics (Metrics of Pratt and Rosenfeld) from the application of the selected edge detection algorithms.*

RESULTED VALUES OF PERFORMANCE EVALUATION METRICS						
Rosenfeld METRIC **CANNY**	Rosenfeld METRIC ROTHWELL	Rosenfeld METRIC **BLACK**	Rosenfeld METRIC SUSAN	Rosenfeld METRIC **LOG-LIN**	Rosenfeld METRIC BEZDEK	Rosenfeld METRIC **EDISON**
0,6697	0,6915	**0,6470**	0,7536	**0,6372**	0,7708	**0,6695**
Pratt METRIC **CANNY**	Pratt METRIC ROTHWELL	Pratt METRIC **BLACK**	Pratt METRIC SUSAN	Pratt METRIC **LOG-LIN**	Pratt METRIC BEZDEK	Pratt METRIC **EDISON**
0,5290	0,4811	**0,4530**	0,5785	**0,5984**	0,4989	0,5340

2.3.2 Case study: KVR-1000 panchromatic imagery – Penteli area, Attica

In addition to the assessment of edge detection procedure to the single-date IKONOS VHR image, the same edge detection algorithms were applied and assessed to a subset of a multi-temporal KVR-1000 imagery (for years 1988 and 1992), which covers the area contained in the maps of the Approved City Plan of Athens. For better visualization purposes, the KVR-1000 images were magnified to give a better aspect of the area of interest. Due to limitation of the paper length, the output images from the application of the Canny algorithm for both dates are presented, in order to prove the sufficient performance of the edge detection methodology and its contribution to change detection.

The remote sensing methodology used for the processing of the KVR-1000 imagery included the following techniques: **(1)** Calculation of the Band Difference Image between both dates, **(2)** Convolution of texture filters (calculation of skewness and variance) with a 3x3 and 5x5 kernel size and **(3)** Production of the "Highlight image" classification map based on the difference image between 1988 and 1992.

In this paper, the output images from processing steps (1) and (3) are presented. More specifically, in Figure 11, is presented the coverage containing the polygons of the forested areas and forests (red colored) according to the Approved City Plan of Athens overlaid on the Band Difference output image of the KVR-1000 imagery. Regions with a high degree of land cover change between 1988 and 1992 appear very bright. In Figure 12 the same polygon coverage (blue outline) is overlaid on the "Highlight Changes" output image of the initial KVR-1000 images, which depicts land cover changes between 1988 and 1992. The "Highlight Change" Image is a five-class thematic image, typically divided into the five categories of "Background" (black), "Decreased" (red), "Some Decrease" (turquoise), "Unchanged" (light green), "Some Increase" (orange), and "Increased" (dark green).

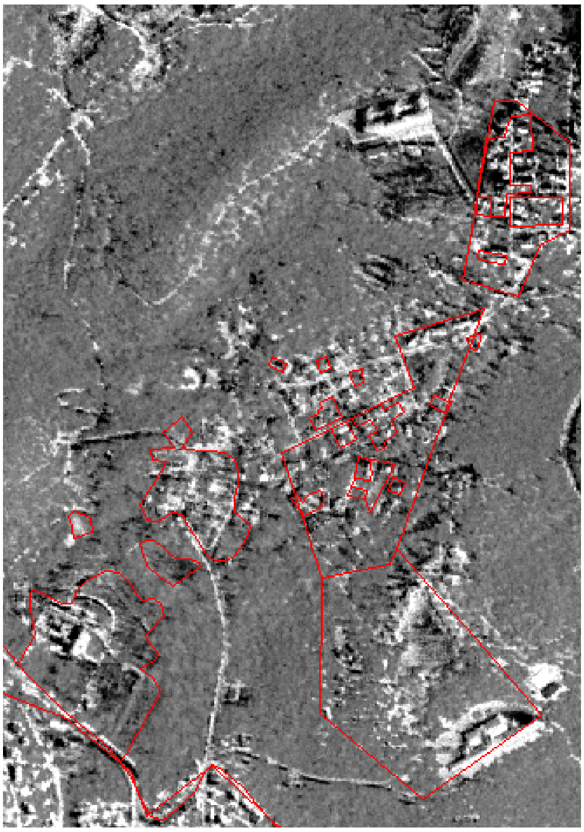

Figure 11: *Overlay of the forest and urban plan coverage (red polygons) on the Band Difference output image of the KVR-1000 images, which depicts land cover changes between 1988 and 1992 (magnified).*

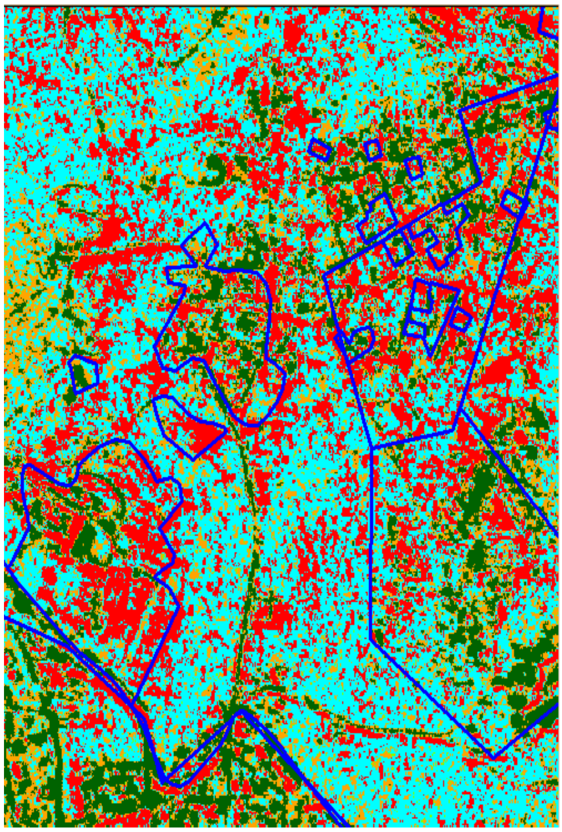

Figure 12: *Overlay of the forest and urban plan coverage (blue polygons) on the "highlight changes" output image of the initial KVR-1000 images, which depicts land cover changes between 1988 and 1992.*

In Figures 13 and 14, on the left are presented the output images derived from the application of the Canny algorithm with input parameters σ=1.5, T_{low}=0.5 and T_{high}=0.9 for the dates 1988 and 1992 respectively, whereas on the right are presented the original KVR-1000 images for both dates. In Figure 13, areas of change appeared with high reflectance values were extracted as connected regions. In Figure 14, areas with high reflectance values (high contrast) are extracted as connected regions, while dark areas (forested) are not extracted. The appearance of urban extension in the period 1998-1992 (red ellipse- delineated area) should also be noticed from the comparison of the output edge maps and the corresponding original KVR-1000 images, for the same time period. In general, it is noticed good extraction of edges (e.g., edges correspond to meaningful image content) in both Figure 13 and 14.

From the analysis of Figures 11-14 it can be inferred that, change detection methods as well optimal edge detection methods are capable of providing adequate information content, either used seperately or in a combination. If there is data provision of a single date, then optimal edge detection can perform stand-alone providing sufficient results to be further introduced to a knowledge-based image analysis system (Figure 1). If multi-date data exist, then change detection methods can be used seperately or alternatively in combination.

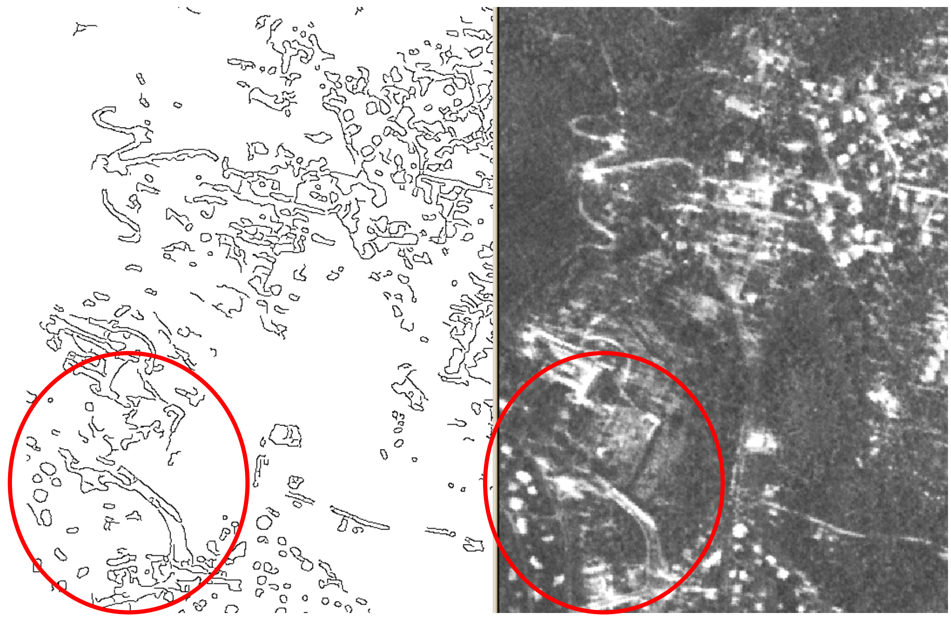

Figure 13: *Left: Output image derived from the application of the Canny algorithm with input parameters σ=1.5, T_{low}=0.5 and T_{high}=0.9. Right: The original KVR-1000 image acquired in year 1988. Note that areas with high reflectance values have been extracted as connected regions.*

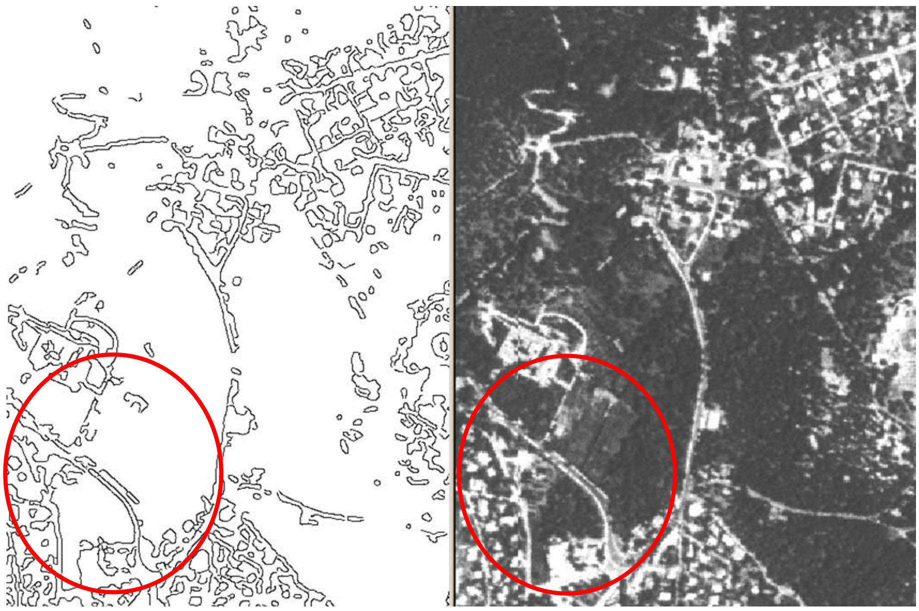

Figure 14: Left: Output image derived from the application of the Canny algorithm with the same input parameters as in Figure 12. Right: The corresponding original KVR-1000 image acquired in year 1992. Note that areas with high reflectance values (high contrast) have been extracted as connected regions, while dark areas (forested) have not been extracted. Also note the appearance of urban extension in the period 1998-1992 (red ellipse-delineated area). In general, it is noticed good extraction of edges (e.g., edges correspond to meaningful image content).

3. RESULTS AND DISCUSSION

From the analysis of the implementation and the **visual (qualitative) assessment** of all edge detection algorithms compared to the results of the photointerpreted ground-truth map of Figure 3, it is inferred that, all algorithms (excluding the *EDISON* and Canny algorithm), poorly extracted those edges of low-contrast features. On the contrary, all edge detection algorithms performed sufficiently the extraction of edges of high-contrast features (Figures 4-10, 13-14). The output edge map of the *EDISON* algorithm could be 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 interpretability 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 “interpretability” 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 could be inserted into a knowledge-based identification system of urban features for the production of the final urban feature thematic map (Figure 1).

From the analysis of the results of edge detection performance evaluation (**quantitative assessment**) it was observed that all edge detection algorithms provided a sufficiently high value range of the Rosenfeld metric (0.63-0.77), which implies that these algorithms extracted edges with good connectivity and edge coherence. Furthermore, resulted values from the *Pratt* metric ranged between 0.48 and 0.57. This implies that a relatively high number of meaningful edges was extracted. On the other hand, for algorithms that did not embedd any thresholding and thinning process (e.g. the Bezdek algorithm), the high value of the Pratt metric could be affected, because the extracted edges of the particular algorithm have edge pixel thickness greater that one pixel and the Pratt metric does not ”penalize” the extraction of redundant edges as in the case of omitted edges.

CONCLUSIONS

One main aspect from applying the edge detection algorithms is their good performance in terms of coherence, edge localization and high edge response, and therefore they provide useful tools towards automated urban / peri-urban mapping.

From the comparison of the output results derived from the application of the Canny algorithm, at different dates, and the change detection maps it was inferred that an optimal edge detection method as well as change detection method are capable of providing adequate information content, either used as stand-alone methods or in a combined with each other (depending on the data provided (single date or multiple dates data) and can be further introduced to knowledge-based systems for extracting only the meaningful information (e.g. building boundaries with very high spatial accuracy of extracted boundary lines, other land cover classes related to informal settlements (e.g. forested areas).

Finally, the application of sophisticated edge detection algorithms could successfully perform as an initial methodological stage where edges can be extracted with high positional accuracy as well as in combination with supplementary remote sensing and GIS methods in order to provide appropriate automated tools for environmental change detection and decision-making based on environmental legislation enforcement.

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