MULTI-SPECTRAL EDGE DETECTION FOR ENHANCED EXTRACTION AND CLASSIFICATION OF HOMOGENEOUS REGIONS IN REMOTELY SENSED IMAGES

Braitbart M., Almog O., Shoshany M.*
Civil Engineering Faculty, Department of Transportation and Geo-Information, Technion – Israel Institute of Technology, Haifa, Israel. Mor.braitbart@gmail.com; (almogo, maximsh)@technion.ac.il

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ABSTRACT:

Mediterranean environments are characterized by high spatial and temporal heterogeneity due to their climatological, lithological, soil and vegetation geo-diversity and their high population density which cause growing land-use transformations at the rural-urban fringe. Remote sensing mapping and monitoring land cover in these environments under such conditions is a challenging task. Instead of the common per pixel approach we suggest combining application of an object-oriented classification based on image objects separation through edge detection with unsupervised classification. The main elements of our methodology are: (1) separating image areas into vegetation/ non-vegetation regions utilizing NDVI threshold; (2) calculation of the spatial variance at different bands; (3) image objects extraction through enhancement of the differences between edge pixels and regions of homogeneity; (4) per-object classification for the homogenous areas; (5) overlaying large unclassified image areas by the results of ISODATA (Iterative Self-Organizing Data Analysis) unsupervised classification. Our methodology was applied on multi-spectral images acquired by the VENμS remote sensing system. The study area consists of a typical rural area in semi-arid climate regions undergoing increasing urbanization. Six test areas were selected representing different spatial combinations of natural/ planted forests, agriculture and built-up land-use/ land cover types. While bare fields were poorly classified, areas of low vegetation cover were classified with producer/user accuracies below 60%, built-up areas and roads, cultivated areas, shrublands and bata (dwarf-shrubs) and rocky areas gained good producer/ user classification accuracies.

1. INTRODUCTION

Remote sensing mapping and monitoring of semi-arid Mediterranean rural environments is important due to high rates of land-use transformation following increase in population density and economic/ industrial activities (Shoshany and Goldshlager, 2001). Climate change is another source of land cover changes with recent indications to the drying of shrublands and planted forests (Shoshany and Karnibad 2011, 2015). These spatio-temporal changes present fundamental challenges to the remote sensing techniques implemented over such complex environments. While per-pixel approaches are widely utilized their use with mid resolution in Mediterranean regions is inherently limited due the existence of spatially frequent surface cover transitions. Object-based approaches are suggested as alternative methodological avenue for mapping and monitoring surface cover changes (Cohen and Shoshany, 2001; 2004). The aim of this study was to develop a new method for extracting image objects representing homogenous areas and to map land cover types following their classification.

2. STUDY SITE AND TRAINING AND TESTING AREAS

Our study site is located at the south-eastern corner of the Mediterranean Sea. It is an area of transition from Semi-arid to Arid climate with natural vegetation varying from woodlands in the north, Bata (dwarf-shrubs and rocky desert terrain an herbaceous plants' growth during the winter. The area is characterized by distinctive agricultural activities with orchards and crop fields and rural settlements. For training and testing there were delineated 8 areas representative combinations of natural, agricultural and built-up areas. Interpretation of 8 land cover categories was done from the VENUS images in addition to Google earth as well as air photographs from the MAP.GOV.IL site.

Figure 1: Study Site in the South Eastern Mediterranean

* Corresponding author.

The land cover categories were: Built-up and roads, water, Natural dense woodlands and planted forests, Open (sparse) shrublands, cultivated agriculture, bare fields, dense shrublands and Bata and rocky terrain.

3. DATA SET

The imagery used for this study site was acquired by VENµS (Vegetation and Environment on a New Micro Satellite) satellite which was launched in August 2017 as the result of an Israeli French cooperation. The satellite is equipped with a multi-spectral camera with 12 narrow spectral bands (Table 1) in the VNIR (Visible Near Infrared) spectral region at 5m ground resolution operating simultaneously.

Bands	Central Wavelength (µm)	Bandwidth (nm)	Main Driver
B1	0.420	40	Atmospheric correction
B2	0.443	40	Aerosols, clouds
B3	0.490	40	Atmospheric corrections
B4	0.555	40	Land
B5	0.620	40	Land
B6	0.620	40	DEM, image quality
B7	0.667	30	Land
B8	0.702	24	Land
B9	0.742	16	Land
B10	0.782	16	Land
B11	0.865	40	Land
B12	0.910	20	Water vapor

Table 1: VENUS Bands

4. METHODOLOGY

The methodology after the pre-processing stage evolves in two parallel processes: image objects segmentation utilizing edge enhancement technique and ISODATA unsupervised classification of Multi-spectral VENUS imagery. The methodology was applied separately for vegetated and bare image areas based on the implementation of a NDVI threshold.

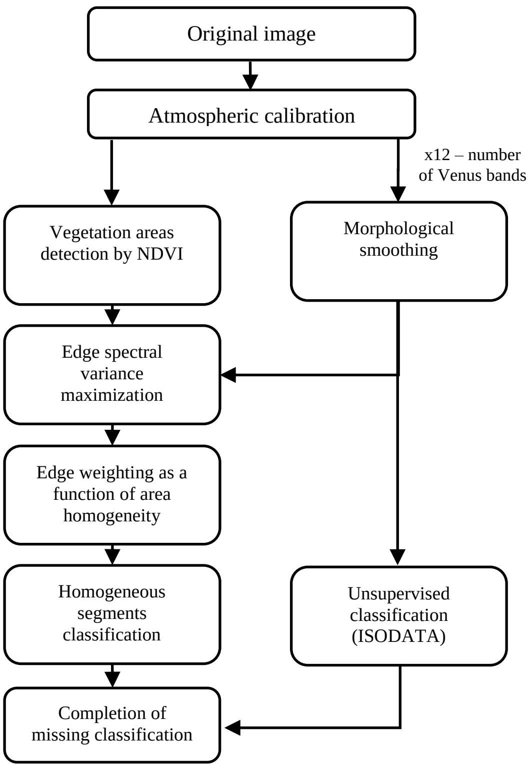

Figure 2: The general research methodology

A threshold value of NDVI=0.2 was selected to differentiate between the two surface cover categories. Prior to the performance of the different tasks there was applied morphological smoothing on all image spectral bands.

4.1 Image objects segmentation and classification

Edge detection is a powerful tool in computer vision, image understanding and pattern recognition (Muthukrishnan and Radha, 2011). Segmentation differentiates between objects by detecting sharp changes in the spectral reflected flux between adjacent pixels. Most segmentation approaches are single band based, or applied on RGB images (Yen, 2003; Sun et al, 2007). Chen et al, suggested to utilize the multi spectral variance in material classification process to detect edges in the multi-spectral domain. Xu et al., suggested to use the change in the spectral signature to calculate edge between pixels in the N dimension spectral image. Here we apply it separately in all VENUS image bands by ccomputing the variance between adjacent pixels was calculate for 3x3 kernels.
Figure 3 shows that the maximum variance (blue) and the minimal variance (orange) recorded between the different bands along an arbitrary chosen profile. This graph indicates that choosing a high threshold value may result lead to missing edges, while choosing too low value will result in the inclusion of noise or local changes within image objects supposed to represent homogeneous areas. Selection of the right threshold was done by trial and error, by assessing visually the results across the whole image.

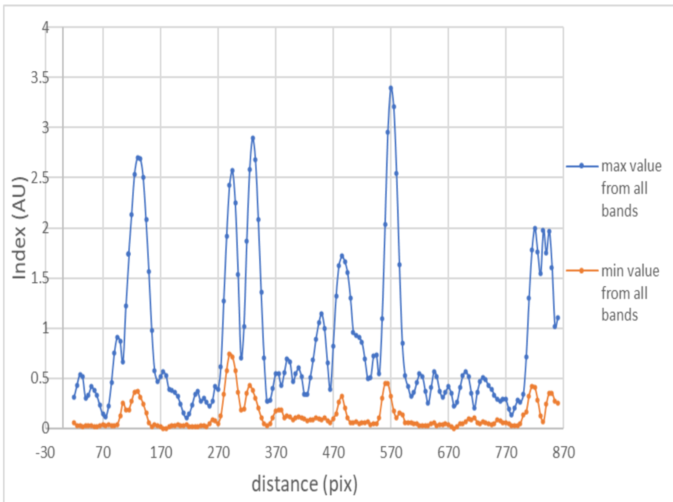

Figure 3: Minimum and maximum variance in a spatial profile after smoothing

To enhance the image homogeneity, the total number of neighbours of each pixel, which were not previously classified as an edge were summed for an 3x3 image kernel. The larger the number of non-edge pixels around an edge pixel (according to the threshold), the greater the weight of the edge.
Following the delineation of the homogenous image homogenous objects there was calculated for each of them the average spectral reflectance vector combined by the different VENUS bands.
A supervised Maximum Likelihood classification was then applied utilizing all the homogenous objects. The Maximum Likelihood method was found to perform better than the SAM (Spectral Angular Mapper) technique utilizing threshold similarity values.

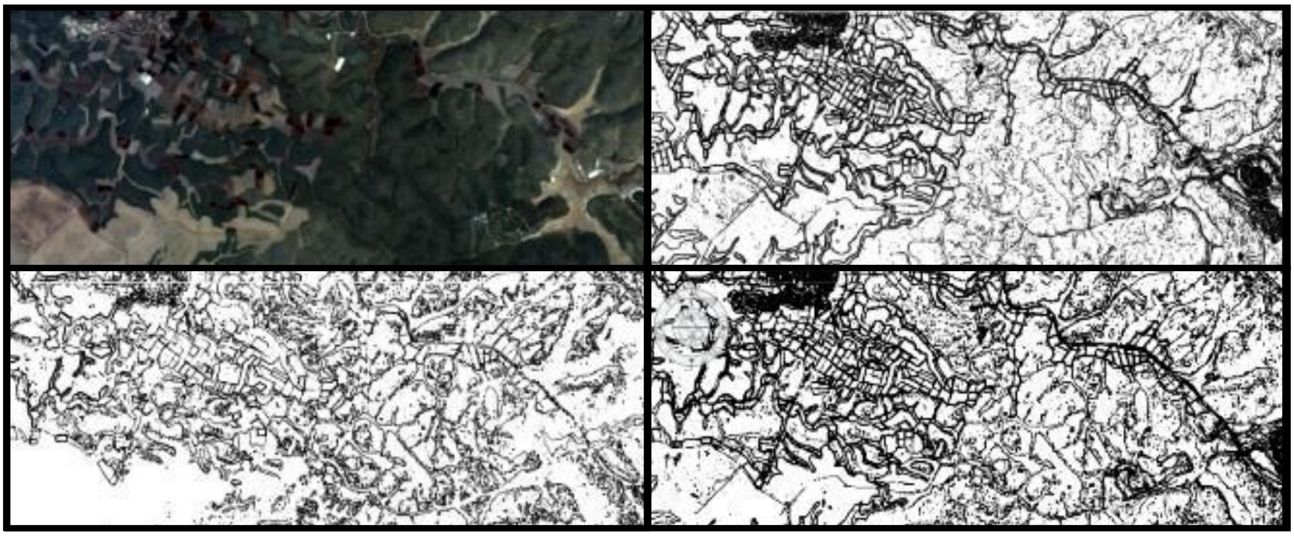

Figure 4: Results of edge detection according to the stages of the method: original image (top left), edge detection in exposed areas (top right), edge detection in vegetation areas (bottom left), edge detection in final image (bottom right)

4.2 Complementary ISODATA classification

For the image areas which were not segmented into objects there was applied ISODATA unsupervised classification. CLUMP method (ERDAS IMAGINE) facilitated grouping contiguous pixels belonging to the same class into image objects, and SIEVE method allowed filtering out small such objects. The supervised categories were recoded according to the results of the ISODATA in the training areas.

5. RESULTS AND DISCUSSION

Figure 4 shows the results of the edge detection for the bare terrain (top right) and vegetated terrain (bottom left), and their combination (bottom right).
There is distinctive expression of the road's networks and of the dense built-up areas. Crop fields and parcels of orchards are also well detected as clusters and individual rectangular objects. However, there is an extensive area which is not separated into sub-areas by edges, the whole area was process as a single object which was classified as an exposed area. To overcome this weakness in the process, the area was completed by the ISODATA classification and was expressed by several classes, represent different land covers.
Figure 5 represents an area of natural and agricultural land uses, while figure 6 presents a typical rural agricultural area with small presence of natural vegetation in the top right corner.
Confusion matrix was calculated for all 8 testing areas. Table 3 presents the results of the producer and user accuracies for the 8 interpretation categories.
Class 6, bare fields got the lower classification accuracies due to its inherent spectral reflectance similarity with rocky bata terrain. The second lowest classification results refer to class 4, sparse shrublands which are also characterised by substantial presence of bare rocky surfaces. Natural dense woodlands and

Class number	category	color
Class1	Roads and urban areas	
Class2	water	
Class3	Natural dense woodlands/ planted forests	
Class4	Sparse Shrublands	
Class5	Cultivated agricultural land	
Class6	Bare fields	
Class7	Dense shrublands	
Class8	Bata and rocky terrain	

Table 2: Description of interpretation categories

planted forests (mainly pine trees) were classified with 79% accuracy (both producer and user). Dense shrublands got good user accuracy (82% and moderate producer accuracy. Again, also in dense shrublands there is presence of rocky patches.
Class 1, roads and built-up areas got very high producer accuracy, while user accuracy was moderate (71%). Built-up areas are characterized by high density of edges: of roads, buildings, yards, shades, gardens etc. etc. which cause high variation at the pixel level classification: there are not detected distinct objects in this pattern. Class 5 cultivated areas are characterized by the best combination of producer and user accuracies (86% and 94% correspondingly).
Overall, considering the wide representation of these 8 land cover categories and their spatial combination, the classification results are good. Utilizing of images from other seasons would un-doughtily allow resolve of some of the confusions, primarily those referring to bare surfaces.

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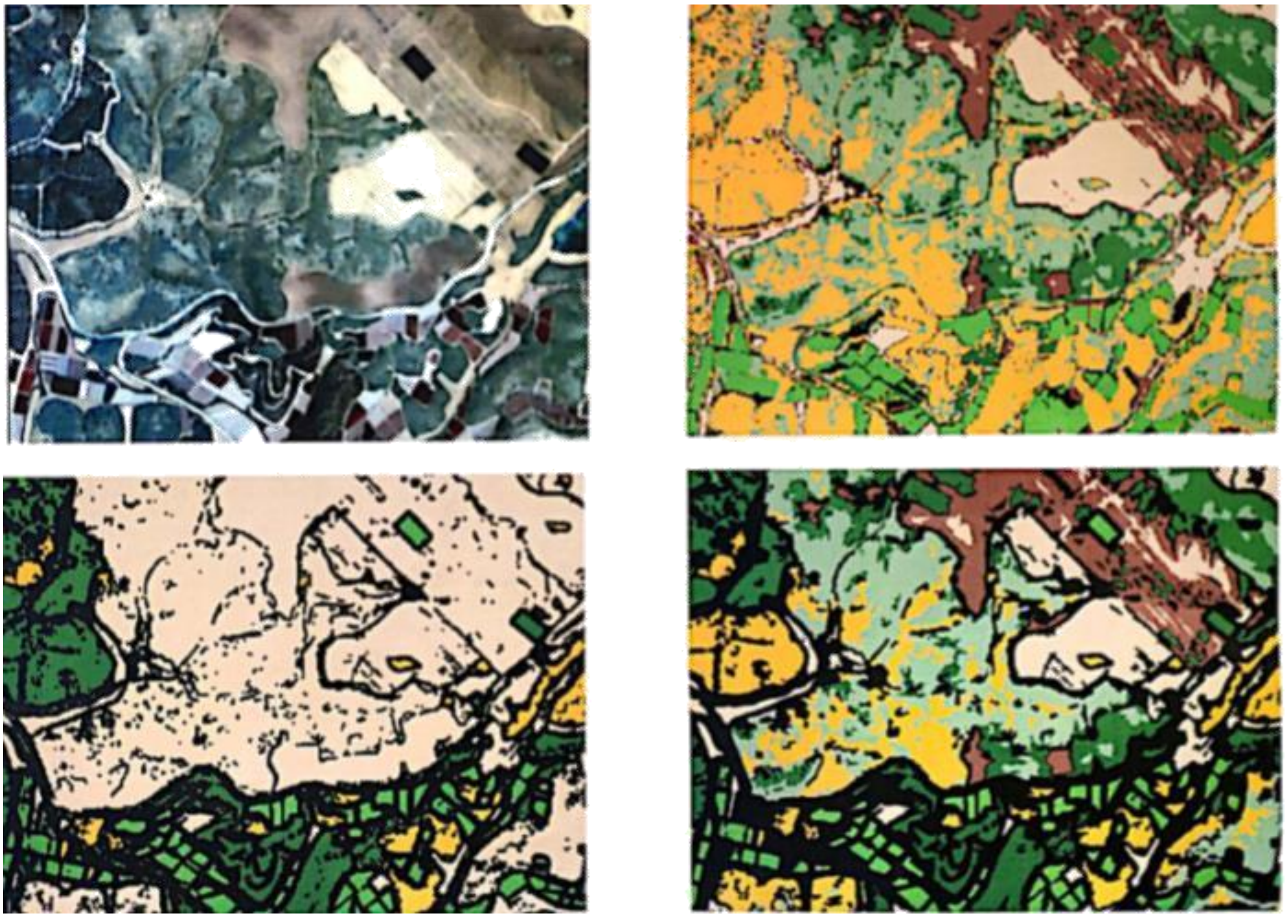

based classified image including completion of missing areas using ISODATA (bottom right)

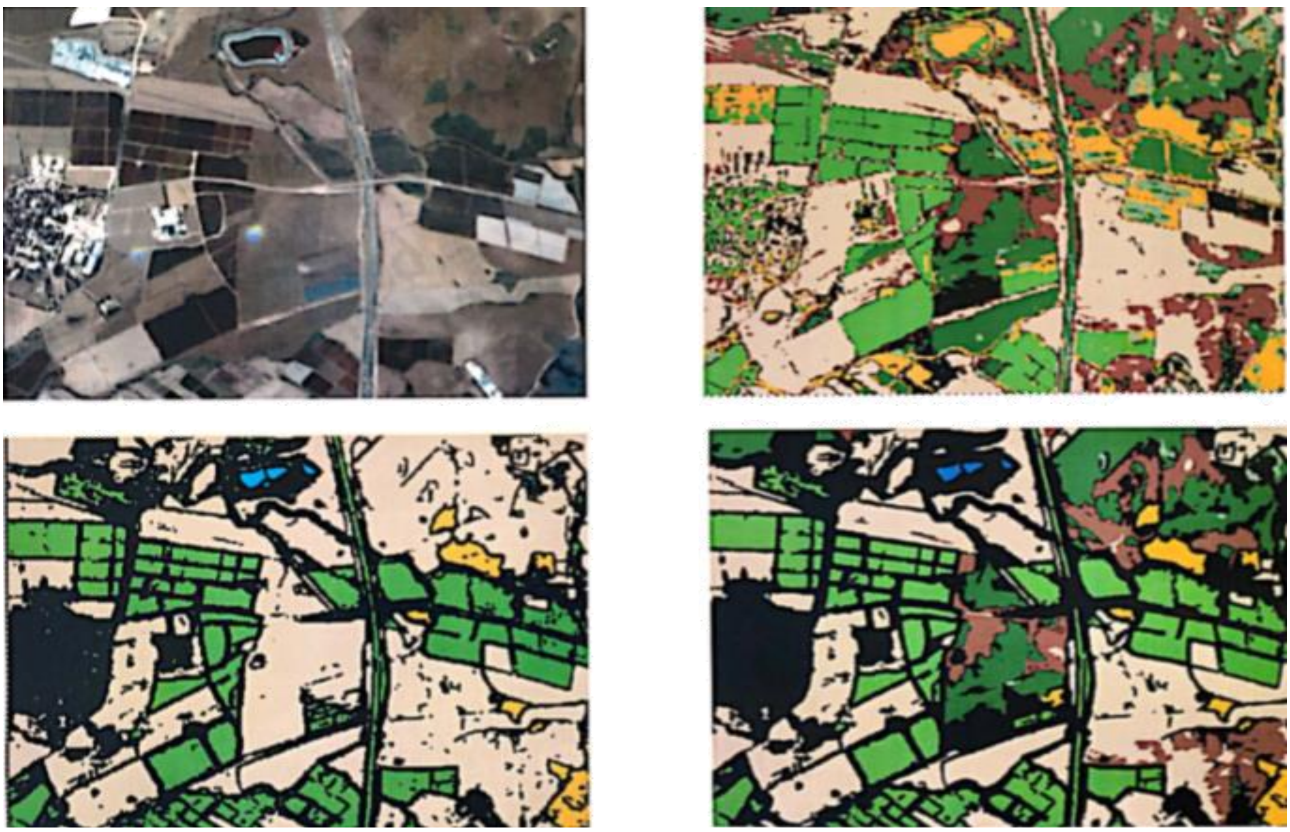

Figure 6: Classification results for second test area. Original image (top left), edges based image classified per-object with ML classification (bottom left), ISODATA unsupervised classification for the original image (top right), final research result – edges based classified image including completion of missing areas using ISODATA (bottom right)

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	Reference total	Classified total	Number corrects	Producers' accuracy	Users' accuracy
Class 1	92	121	90	97.83%	74.38%
Class 2	13	9	9	69.23%	100.00%
Class 3	55	54	43	78.18%	79.63%
Class 4	22	16	12	54.55%	75.00%
Class 5	78	71	67	85.90%	94.37%
Class 6	29	15	6	20.69%	40.00%
Class 7	45	39	32	71.11%	82.05%
Class 8	66	67	32	78.79%	77.61%
Total	400	400	311		

Table 3: Analysis of reliability and accuracy results from the confusion matrix for the edges-based image classified by ML method.

5.1.1 Entropy analysis:

Entropy is a measure of the effective size of a probability space. It is common to think of entropy as the degree of disorder of the system, or as the degree of randomness in it. It is calculated utilizing Shannon Weiner Information index.
Analysing the classification results, the entropy index represents the amount of fragmentation in the classified imaging. The more fragments there are, there are more smaller areas with different classification, indicating the classification is noisier.
Table 4 presents the results of the entropy index calculation for each of the test areas as calculated in the final classification image based on the edges image. The entropy obtained for the original image classified by the ISODATA method is higher, for each of the test areas (AOIs). The largest gap is in test area No. 6 where there is a difference of 2.055. This area is mostly agricultural areas that are characterized by their rectangular form and their high sub-division by edges. In addition, the classification results for agricultural areas in this study were very accurate, these facts explain the significant gap in this test area.

AOI	Entropy index for unsupervised classification image	Entropy index for classified edges image
AOI 1	2.679	1.623
AOI 2	2.648	1.846
AOI 3	2.155	2.045
AOI 4	1.977	1.143
AOI 5	2.673	1.407
AOI 6	3.258	1.203

Table 4: Entropy index for each test area

6. CONCLUSIONS

A new approach of land cover mapping, under heterogeneity conditions was presented. Advanced image processing techniques applied for this purpose, including multi band segmentation and multi spectral classification utilizing per-object approach.
A multi spectral approach was developed for defining edges as strips which separate relatively homogenous image regions, representing transition zones characterized by mixtures of adjacent land covers.
For the quantitative evaluation of the results, the use of confusion matrix facilitated estimating the overall accuracy and the calculation of the entropy (Shannon Information) of the classified images allowed calculation of the degree of order/ disorder of the classified image. Reliability and accuracy of the classification and the calculated entropy index for the edge-based image showed good results compared to an unsupervised classification of the original image using the ISODATA method.
The method demonstrated qualitative results in the discovery of different types of edges (main roads, random roads, trails, transition between different types of parcels) for agricultural areas, exposed areas, and areas of natural vegetation of varying density. The methodology showed good performance separating agricultural parcels and relatively homogenous bare surface areas. In vegetated areas, the algorithm showed lower efficiency and was affected by the variability resulting from different shading and vegetation combinations. Separating the vegetation areas from bare areas with low vegetation coverage, utilizing the NDVI index was found instrumental in gaining overall improvement in the classification results. A major advantage of the method is in detecting urbans areas as unified clusters; This capability is very effective for detecting mapping urbanization processes, using satellite imagery with high spectral and spatial resolution, such as provided by the VENUS sensing system.
Further testing and developing the method with multi-date imagery is required.

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