Semi-Automatic Object-Based Building Change Detection in Suburban Areas from Quickbird Imagery Using the ERDAS Imagine Objective Software

Georgios Karagiannis and Demetre Argialas
National Technical University of Athens, School of Rural & Surveying Engineering, Remote Sensing Laboratory, Athens, Greece;
giorkarag@gmail.com, argialas@central.ntua.gr

Abstract. This paper aims at effectively detecting the building changes in bi-temporal very high resolution satellite images. Many applications require detecting structural changes in a scene over a period of time. Change detection of man-made objects using remote sensing images has many applications such as city planning, informal building detection and disaster management. For this paper, two bi-temporal multispectral images from the QuickBird satellite are used, depicting a region of south-eastern Attica. The implementation of the semi-automatic change detection of the two images is made in the object-oriented environment of the ERDAS Imagine Objective. The method is based on the comparison of two independent classifications. The independent building extractions are the result of tree-processes in the Objective. The first step for each feature extraction in Objective involves the system training by defining background and non-background training samples. Afterwards, Objective creates a probability layer which presents the single probability of each pixel for being a building, based on the training samples. Then, the creation of objects is followed by a raster object operator such as segmentation. Subsequently, the created objects are processed by applying a variety of functions including probability, size or morphological filters. This is the last raster level since the next level converts the objects from raster to vector form. Consequently, the objects are processed by operators which reshape the existing objects, eliminate these who do not meet certain criteria, combine multiple objects to a single or split object into multiple new vector objects. The next level is to perform classification on the vector objects. Vector object classification involves specifying one or more cues which are used by the Object Classifier. Cues include metrics which certain properties of vector objects are measured. The Object Classifier uses the cues to assign a probability to each object in a group of vector objects. Finally, the last level includes operators which typically clean up the set of vector objects to produce a nice final output. Some Vector Cleanup Operators use the probability attribute generated by the Vector Object Processor in the operation. The implementation of the change detection is carried out by the comparison of independent building extractions using an operator that computed the probability of change for every object, taking into consideration the probabilities of the objects for both dates, and the distance of centroids of the polygons between the two dates. The results of extraction are very satisfactory since the correctness is 85.9% and 85.2% and the quality 67.0% and 67.5% for the first and second dataset respectively. The change detection do not produce proportionally successful results since the correctness is 22.3% and the quality 13.4%. The reasons which contribute to the lesser accuracy of the change detection results are primary, due to the mediocre geometric registration of two images, the limited spectral information of the data as well as the large extent and complexity of the study area.

Keywords. Semi-automatic change detection, object-based image analysis, automatic building extraction, satellite imagery, QuickBird, ERDAS Imagine Objective, informal settlements.

1. Introduction

In Greece, there are approximately 6.9 million residences for a population of 11 million. A rough recent estimation by the general inspector of the Ministry of Environment, Physical Planning and Public Works shows that, in total, the informal settlements in Greece are up to 1,000,000 residences

[1]. According to the existing legal framework, as "informal construction" in Greece is characterized any construction which exists without a building license, has any kind of excess or violation to the building license or is in violation of any valid urban and spatial regulation, regardless of the existence of a building license [2]. According to a statistical study [3] for the period 1991-2001, approximately 93,000 legal and 31,000 informal residences were constructed each year, 40% of them are in the area of Attika. According to the available national statistical data, 122,148 legal residences were build in 2004 and 116,963 for the first 10 months of 2005. It can be estimated that approximately 40,000 buildings without building licenses are build every year, 16,000 of them in the area of Attika. This is equivalent to the size of a small town.

The systematic monitoring of candidate regions with ground control would be extremely costly and time consuming. The solution can be provided by Digital Remote Sensing and Digital Photogrammetry with automatic change detection. Using satellite images periodically for areas deemed dangerous for such construction ensure the timely observation of the phenomenon and in addition with an appropriate legal framework, to prevent it.

For this paper, two bi-temporal multispectral images from the QuickBird satellite were used, depicting a region of south-eastern Attica. The first was taken in August 2004 and the second in April 2006. They have 60 cm resolution on panchromatic and 2.4 m on multispectral.

1.1. Change detection methods

Researchers involved in change detection studies using satellite images have conceived a large range of methodologies for identifying environmental changes. Change detection procedures can be grouped under three broad headings, characterized by the data transformation procedures and the analysis techniques used to delineate areas of significant changes: (1) image enhancement, (2) multi-date data classification and (3) comparison of two independent land cover classifications [4]. The enhancement approach involves the mathematical combination of imagery from different dates such as subtraction of bands, rationing, image regression or principal components analysis (PCA) [5]. Thresholds are applied to the enhanced image to isolate the pixels that have changed. The direct multi-date classification is based on the single analysis of a combined dataset of two or more different dates, in order to identify areas of changes.

The post-classification comparison is a comparative analysis of images obtained at different moments after previous independent classification. This is the most obvious method of change detection which requires the comparison of independently produced classified images [4]. By properly coding the classification results for times *T*, *T1* and *T2* the analyst can produce change maps which show a complete matrix of changes. In addition, selective grouping of classification results allows the analyst to observe any subset of changes which may be of interest. Post classification comparison holds promise because data from two dates are separately classified, thereby minimizing the problem of normalizing for atmospheric and sensor differences between two dates [6]. However, if one considers the land cover classification generated from a single date of Quickbird data, it is not difficult to see that the change map product of two Quickbird classifications is likely to exhibit accuracies similar to the product of multiplying the accuracies of each individual classification (Singh 1989). Hence, it can produce a large number of erroneous change indications since an error on either date gives a false indication of change.

In the present study, the change detection procedure was based on the post-classification comparison of two independent building extractions using the ERDAS Imagine Objective.

1.2. Imagine objective

Objective is an additional tool on the ERDAS Imagine platform. Imagine Objective provides tools for feature extraction, update and change detection, enabling geospatial data layers to be created and maintained using remotely sensed imagery operating supervised classification. The software combines inferential learning with expert knowledge in a true object-oriented feature extraction environment. The object-oriented approach enables the software to emulate human visual processing by analyzing data not just on a pixel by pixel basis but also by looking at object-based measures such as shape, size, texture, shadow, association and more. The software also encapsulates vector processing operators to produce data which can be used in a GIS with minimal post processing.

The program supports both discrete, single feature object detection as well as multi-class, wall-to-wall object-based classifications. Imagine Objective has been successful extracting single feature objects including residential rooftops, commercial and industrial buildings, road centerlines and/or ribbons, tree crowns, automobiles, boats, and military targets, such as airplanes and tanks, to name a few. Multi-class wall-to-wall classifications are supported for general land cover mapping and vegetation mapping applications. Subsequently, this study is based on single feature object detection because it is more accurate and it permits more operators.

It has a specific process flow, composed of seven levels. Each level is being processed using one or more operators, depending on the level. The order that the program performs each level is specific and unchangeable, but the order of the operators inside each level can be modified by the user. The seven levels are:

1) <u>Raster Pixel Processor (RPP)</u>
   The Raster Pixel Processor node performs pixel level image classification. This is normally the first process node in a feature model [7].

2) <u>Raster Object Creators (ROC)</u>
   Raster Object Creation Operators create sets of raster objects from input raster data. These operators form groups of pixels from the input raster data, and identify each distinct group of pixels by assignment of a unique output value which identifies the raster object [7]. The raster objects may be created directly from the input pixel probability layer, or they may have other raster inputs from which the raster objects are created.

3) <u>Raster Object Operators (ROO)</u>
   Raster Object Operators allow the user to manipulate the raster objects created by the Raster Object Creator. The Raster Object Operator may perform a variety of functions on the Raster Objects including: Expanding or shrinking the existing *Raster Objects*, eliminating raster objects that do not meet some criteria, combining multiple input raster objects into a single raster objects, splitting input raster objects into multiple new raster objects, renumbering the raster objects to eliminate gaps after a filtering or eliminating operation [7].

4) <u>Raster to Vector Converters (RVC)</u>
   Raster to Vector Conversion Operators convert sets of raster objects to sets of Vector Objects. The set of Vector Objects produced may be either Polygons or Polylines.

5) <u>Vector Object Operators (VOO)</u>
   Vector Object Operators allow the user to manipulate the vector objects created by the Raster to Vector Conversion. This operator may perform a variety of functions on the vector objects including: Reshaping the existing *Vector Objects*, eliminating vector objects that do not meet some criteria, combining multiple input vector objects into a single vector object, splitting vector objects into multiple new vector objects [7].

6) Vector Object Processor (VOP)
   The Vector Object Processor node performs classification on vector objects. Vector object classification involves specifying one or more cues which are used by an *Object Classifier*. The cues include metrics which measure some property of vector objects. The Object Classifier uses the cues to assign a probability to each object in a group of vector objects [7].

7) Vector Cleanup Operators (VCO)
   Vector Cleanup Operators allow the user to manipulate the Vector Objects after they have been processed by the Vector Object Processor. Vector Cleanup Operators typically clean up the set of vector objects to produce a nice final output. Some Vector Cleanup Operators will use the Probability attribute generated by the Vector Object Processor in the operation. Some typical operations: Reshaping the existing vector objects for a more presentable output, Eliminating *Vector Objects* that do not meet some criteria or that have low probability, matching vector objects to a template or fitting them to a fixed shape or shape type such as an orthogonal polygon, combining multiple input Vector Objects into a single vector object, splitting vector objects into multiple new vector objects, Converting polygon objects into polylines, and vice-versa [7].

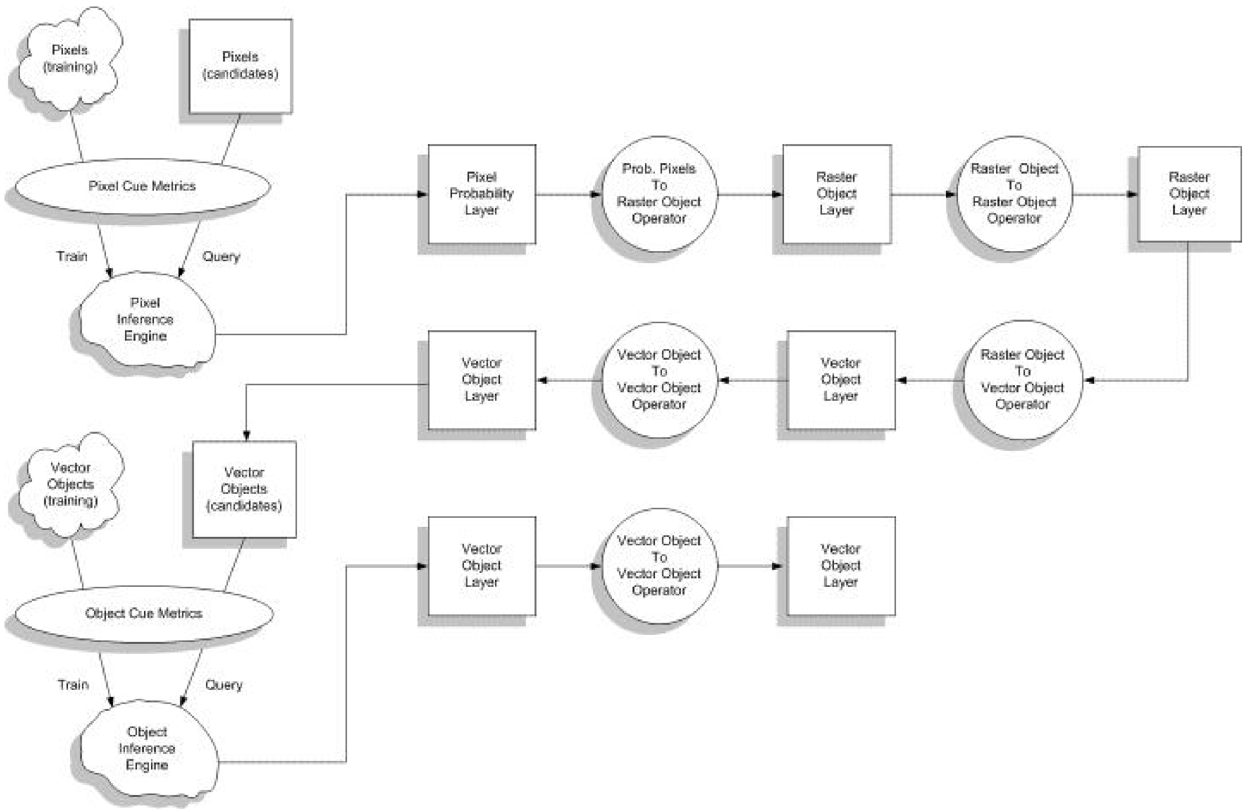

Figure **Error! Style not defined.**1: Objective process flow diagram [7].

2. Methodology

Before the presentation of the object-oriented analysis, should be mentioned some key points of the methodology.

The process of the whole image was proved time-consuming, since sometimes the software needed many hours to perform one single operator despite the fact that the computer met the software requirements. Therefore, it was imperative to split the image into subsets, as the achievement of the ideal feature extraction model requires continuous experimentation on choosing the right operators and the ideal values of their parameters. Moreover, splitting a whole scene into subsets is often suggested [8], [9], [10], [11], [12], [13], [14]. Hence, each image was split into four, equal size, subsets.

Furthermore, the change detection process in the Objective environment can be carried out in two approaches:

The first one means a simultaneous process of the two images as different layers. In the first level the user trains the feature model with training samples. The user, after a quick look at the images, defines as positive samples areas where there have been changes and as negative samples, no change areas. Then, the user performs the other six levels in order to remove all the background objects and finally remain only the changes.

On the other hand, the second approach is the comparison of the results of two independent building extraction models using the “Polygon Change” operator of the VCO level. This way proved more time-consuming but much more reliable. In addition, that’s the proposed approach for detecting changes by the software since, Objective is primary a feature extraction tool. Thus, the second approach is the one that was followed in this study.

Another key point that has to be noted is that the Objective’s strength is maximized on single class models (building/not building). Moreover, the study area consisted mainly of buildings, halved in quantity, which had either tile or concrete roofs. These two classes have utterly different spectral characteristics and each one has background classes that extremely resemble (e.g. roads for the first and soil for the second one). Hence, it was deemed appropriate to create different building extraction models for tile roofs and for concrete roofs. Otherwise, the separation of the background objects that have similar spectral characteristics proved almost impossible by the software and as a result, high commission errors and very low correctness indicator of the procedure. On Figure 2 and Figure 3 the similarity of spectral characteristics between rooftops and background areas are noted.

Figure 2: Spectral variety of tile roofs (top row) and background areas with very similar spectral characteristics (bottom row) of the study area.

Figure 3: Spectral variety of concrete roofs (top row) and background areas with very similar spectral characteristics (bottom row) of the study area.

To sum up, two building extraction models for each of the four subsets of each image (tile roofs-concrete roofs) were created. Consequently, a total of sixteen building extraction models were created.

In addition, there were available two vector format files (.shp) for the assessment of the results. These files were result of analytical and reliable photo-interpretation. The one included the existing buildings of the first date and the other the changes of the second date. The results of the building extraction models of each image were merged in order to produce one single building extraction file for each date. This process was carried out in the environment of the Quantum GIS software.

Afterwards, the two merged files were input data of the “Polygon Change” operator (the VCO level operator of Objective that detects the changes among two images). The exported file of this operator was the final result of the study. The exported file was compared with the photo interpreted data in the Quantum GIS. This software performs comparison of the polygons among two files and without shape criteria (even with marginal overlap) shows in an attribute table of the polygons those of the first file that coincide with the corresponding of the second. This criterion was selected to be strict; therefore the file comparison was performed twice. The first time to find out which polygons of the exported file coincide with the photo interpreted polygons and a second one vice-versa. Thus, if one of the exported polygons was overlapping with more than one polygons of the photo-interpretation, it was ensured that in the result would be considered only one successful detection and not more. The same comparison process was followed to evaluate the building extraction results for each date.

The implementation of each subset performed with similar approach, using similar operators and similar parameter values in order to develop a unified model that can extract buildings and detect changes in images with similar characteristics without many changes. More specifically, a brief description of the methodology on each level of the software is following:

1) Raster Pixel Processor (RPP)

At this level, training samples were created in order to carry out the -pixel level- image classification and the probability layer. For the first image, 123 non-background samples and 91 background samples were used and for the second 134 and 83 respectively. This level was performed with the Single Feature Probability cue metric in all 16 feature models. Single Feature Probability (SFP) is a pixel cue that computes the probability metric (a number between 0 and 1) to each pixel of the input image based on its pixel value and the training samples. Higher probability values are assigned to those pixels whose values are similar to the ones of pixels in the non-background training samples. Lower probability values are assigned to pixels whose values are either similar to the ones of pixels in the background training samples or significantly different from the values of pixels in the non-background training samples. In Figure 4, the probability layer on a part of subset 2 of the first image is presented, that was created by the RPP model. In this image it is noted the high probability of the roads as they are white.

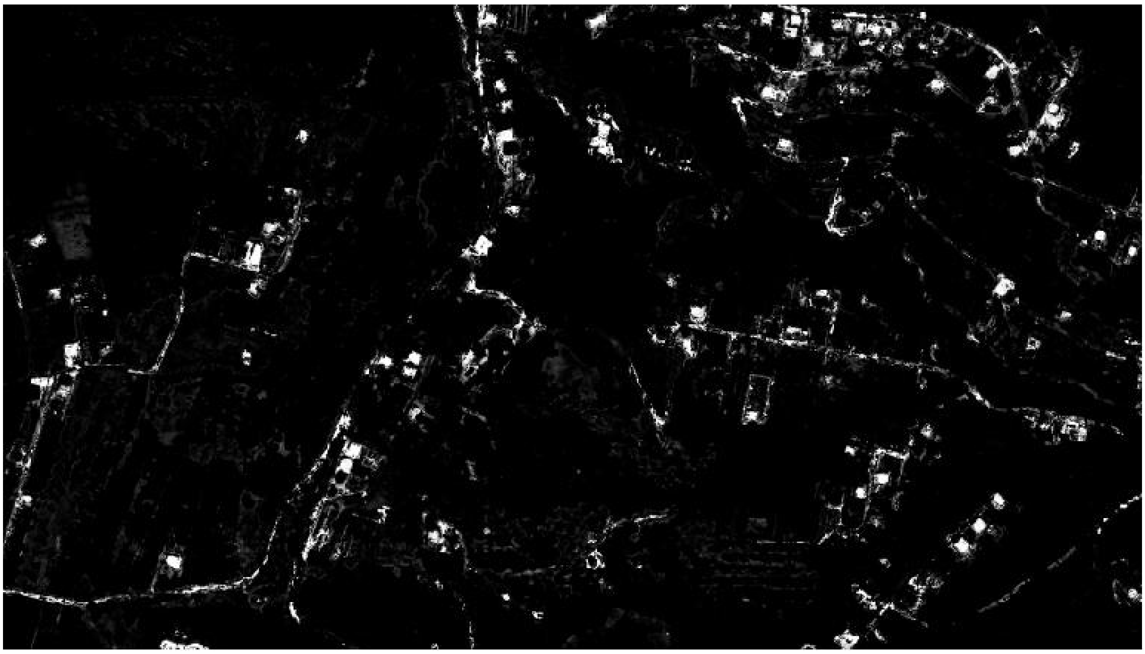

Figure 4: Final result of concrete roof extraction model on part of subset 2 of the first image.

2) Raster Object Creators (ROC)

At this level the raster objects were created using the "segmentation" creator for all feature models. Segmentation is a way of partitioning raster images into segments based on pixel values and locations. Pixels that are spatially connected and have similar values are grouped in a single segment. This operator performs segmentation on the raster image specified by the Input variable parameter. The result is a thematic image where pixel values represent class IDs of contiguous raster objects. The Pixel Probability Layer input (product of the previous level) is used to compute the pixel probability zonal mean of each segment and that zonal mean was used as the value of the segment Pixel Probability attribute. In Figure 5 is presented the result of segmentation.

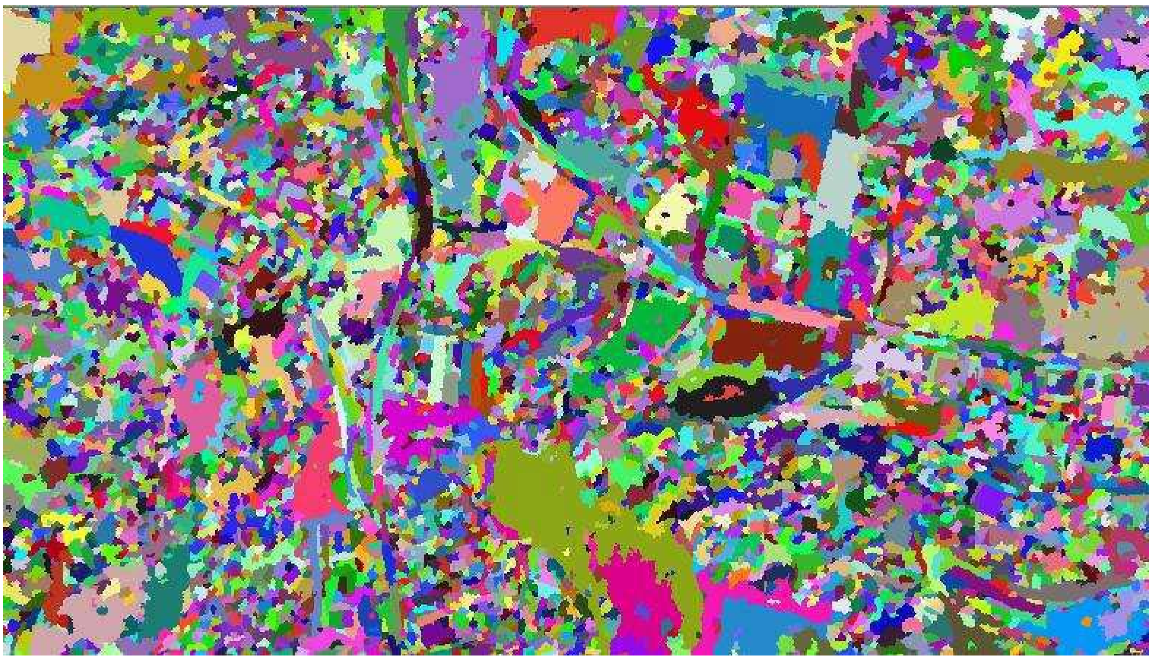

Figure 5: Final result of concrete roof extraction model on part of subset 2 of the first image.

3) Raster Object Operators (ROO)

Afterwards, the processing of the objects created previously followed, using several operators. Size filter and probability filter were used in order to filter out very small, very big and low probability objects. Moreover, morphological filters like dilation and erosion implemented so as to include (or remove for erosion) pixels that belong (or not) to the raster object. Finally, the “reclump” operator was very useful to perform a clump operation. The input layer of this operator is usually a layer of raster objects which have been split, joined or filtered by other operators, and no longer have correct clump values. This operator renumbered the raster objects so that each raster object (group of contiguous pixels) has a unique value. In Figure 6 is presented the final result of ROO level on part of subset 2 of the first image.

Figure 6: Final result of concrete roof extraction model on part of subset 2 of the first image.

4) Raster to Vector Conversion (RVC)

At this level the objects automatically were converted by the software from raster to vector format.

5) Vector Object Operators (VOO)

At this level, the objects were processed by several operators, in vector format this time. Because of the previous processes some of the objects had little islands or holes inside them. Therefore, the Island Filter operator was used in order to remove them. In addition, some objects were overlapping more than one building that had common border. The split operator split these objects so as to correspond one object to one building. Moreover, all the objects had complex shapes with too many vertices. The Generalize operator was used in order to simplify the polygons by removing unnecessary vertices and the Smooth operator in order to smooth their shape. In Figure 7 is noted the final result of VOO level on part of subset 2 of the first image.

Figure 7: Final result of concrete roof extraction model on part of subset 2 of the first image.

6) Vector Object Processors (VOP)

This is the semifinal level of the procedure. The purpose of this level is to redefine the probabilities of the remaining objects along with some shape criteria and parameters that user defines. The criteria that were useful for this study were primarily the axis 1/axis 2 ratio and also perimeter, rectangularity and compactness. The axis ratio was used so as to create low probabilities for the roads than high that they had because of their spectral similarity with the concrete roofs. Also, rectangularity and compactness were used in order to maximize the probabilities of building-objects. This level doesn’t remove any object, just creates new probabilities for the final level.

7) Vector Cleanup Operators (VCO)

At the last level, some objects that remained from the other levels without being buildings were removed using a probability filter based on the new probabilities that ensued by the previous level. In addition, the “orthogonality” operator was used to form orthogonal shapes on the objects, which is the real shape of the buildings. In Figure 8 is presented the final result of a concrete roof extraction model on part of subset 2 of the first image.

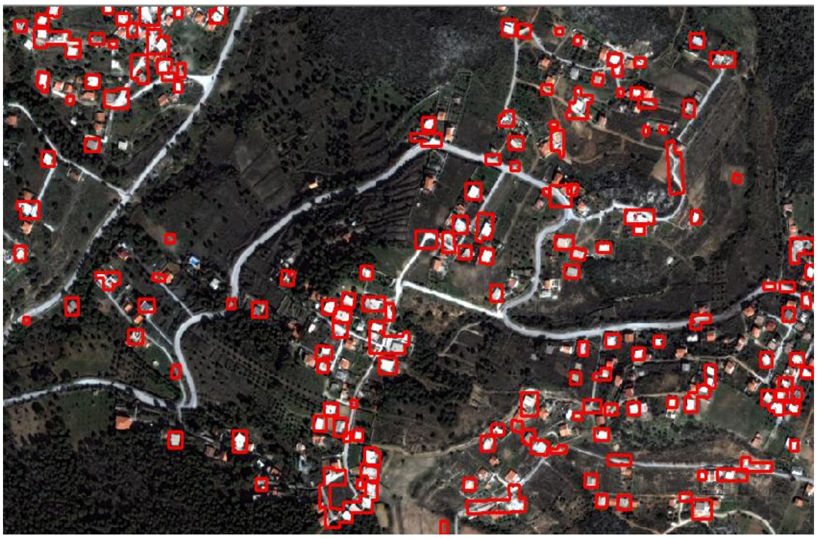

Figure 8: Final result of concrete roof extraction model on part of subset 2 of the first image.

2.1. Change detection

The change detection as mentioned in the last chapter performed using the "Polygon Change" operator from the VCO level. Before performing the change detection it was necessary to merge the eight building extractions of each image to one (one for tile roofs and one for concrete roofs for each of the four subsets of each image). This process occurred at Quantum GIS Environment and the result was two vector format files (.shp), one that included 1,271 objects for the first image and a second with 1,425. Thereafter, these two files were input data of "polygon change" operator. The first one was the pre-existing objects and the second one the model generated. The result was a file that included 121 objects as changes.

3. Results and accuracy assessment

The feature extraction and change detection assessment accrue with the calculation of some indicators. In vector data, accuracy indicators can be measured by checking the coincidence of model extracted polygons with the test data polygons. Hence, True Positives (TP) are polygons (objects) that are correctly detected, False Positives (FP) are the polygons that erroneously have been detected by the model as buildings/changes and False Negatives (FN) are the polygons that mistakenly have not been detected by the model. In this process, there are no shape criteria but even with a marginal overlapping a polygon is considered right. Based on these measurements, according to Equation 1 completeness, correctness and overall quality of the model were computed [13], [15], [16], [17], [18], [19].

$$
\begin{aligned}
\text{Completeness} &= \frac{\text{area of correctly detected segments}}{\text{area of the ground truth}} \\
&= \frac{TP}{TP+FN} \\
\text{Correctness} &= \frac{\text{area of correctly detected segments}}{\text{area of all detected segments}} \\
&= \frac{TP}{TP+FP} \\
\text{Quality} &= \frac{TP}{TP+FP+FN}
\end{aligned}
$$

Equation 1: Indicators of completeness, correctness and overall quality.

Hence, the right and wrong polygons of the model are measured and the omission and commission errors of the procedure are calculated. The omission error was computed by dividing the number of polygons that were not detected by the model (False Negatives) with the theoretically correct number of polygons that have arisen by the test data (photo-interpretation). The commission error was computed by dividing the erroneously detected polygons (False Positives) with the correct number of polygons (photo-interpretation).

These data were the result of photo-interpretation by an experienced photo-interpreter. For the achievement of the assessment, six comparisons were made, two for the extraction of the 2004 image, two for the extraction of the 2006 image and two for the change detection. Finally, the results were imported into a spreadsheet where the calculation of the indicators and errors that mentioned above took place. *Table 1* shows the final accuracy of the procedure.

Table 1. Assessment indicators and analysis errors.

Assessment	Omission errors (%)	Commission errors (%)	Completeness index (%)	Correctness index (%)	Quality index (%)
Buildings 2004	21.9	12.8	75.3	85.9	67.0
Buildings 2006	19.3	14.0	76.5	85.2	67.5
Changes	74.8	87.9	25.0	22.3	13.4

4. Discussion and conclusions

4.1. Discussion

The results of the building extractions are very satisfactory considering the size of the study area, the spectral range of buildings, the complexity of some roofs, the high spectral similarity of some background areas with rooftops and the availability of only four channels. Because of the extent of the area, distant buildings with similar roofs varied widely.

Moreover, some properties of the test data hampered the accuracy of the final result. These properties relate to the detection of buildings that is almost impossible to be detected even by the human eye. Such buildings were either too small or were nearly covered by surrounding objects and possibly detected by ground control. Another issue was that there were several roofs that were detected by the model but were not included in the test data. It should be mentioned that there were a few of these buildings, especially of the first class. In Figure 9 some cases of these problems are noted.

Figure 9: Discrepancies between the feature model and test data. At the first row are noted cases of buildings that are almost invisible and the photo-interpreter detected (Cyan polygons). At the second row are noted example of buildings that the photo-interpreter didn't detect but the model did.

In general, in the analysis and description of a complex environment are expected inaccuracies to occur. Much effort was paid in order to eliminate or shrink errors, with multiple tests on the parameters of each operator, observing their influence on the final result. In all feature models, was a point where the user had to decide either to remove background objects, in addition with buildings that have similar characteristics and probabilities with them resulting omission errors or keep them provoking commission errors. For example, all concrete roof extraction models included the Axis 2/ Axis 1 ratio from the VOP level in order to remove the roads which had very high probabilities. However, despite the fact that roads are long and narrow objects and such a criterion would easily identify them, in reality, segmentation almost every time did not extract the roads as whole objects but as small segments. In most cases, these segments were rectangular with normal axis 2/axis 1 ratio similar to buildings hence it was very difficult to separate them.

The change detection results were not satisfactory. A number of factors related to the complexity of the study area, reduced the final accuracy of the model. In addition to the spectral limitations set by the nature of the data, many difficulties came up because of the insufficient geometric corrections applied to the images. Due to the lack of absolute coincidence between the two images, some geometrical shifts were detected incorrectly as changes, while in fact they were geometric correction inaccuracies.

Consequently, areas that were detected as background in the extraction model of the first date, in the extractions of the second they were identified as buildings and therefore were qualified as changes while these areas were and remained buildings. Thus, many commission errors came up.

Furthermore, the “shifts” mentioned above also appeared because of the height of the buildings and relief distortion. These two sources of errors are related to the data, partly because of their quality and the models that were used for the geo-correction and partly because of the different orbit point and slope at the moment of the capture of each image by the satellite. These limitations could be overcome by the production of true-ortho images, which requires additional data that were not available in this case study.

Moreover, the main disadvantage of the method comparing independent classifications is the transfer of errors duplicated at the change detection process. Additionally, it is noted that the 12% of changes on test data were included at the omission errors of the extraction model of the second date, mainly because most of them were very small objects. Therefore, these buildings could not be detected by the change detection process.

Finally, the accuracy of the final results was affected by the different approach of change definition between the test data and the models. In test data, the material change of a roof considered as change, in fact, these changes were the 25% of the total. This kind of change by default could not be detected by the present approach used. Moreover, the vast majority of changes identified in the control data were small extensions to existing buildings. Such changes are almost impossible to be detected with this data resolution. If the polygon of the detected building of the first date exceeded in size real building limits, it will have overlap with the extension of the building at the second date and therefore it won’t be detected as change by the change detection model.

4.2. Conclusions

In the present study, change detection of building in suburban area with the method of comparison of independent classifications between bi-temporal very high resolution satellite images of Quickbird using the Leica Geosystems software, ERDAS Imagine Objective were investigated. To sum up, at the end of the whole process the following conclusions can be presented:

- ✓ The object-oriented processing and satellite image analysis is the most appropriate. With the existence of numerous high resolution data, the properties of objects offer a wide variety of useful information that is not wise to be ignored.
- ✓ The extraction of anthropogenic features such as buildings that have similar spectral properties with background areas requires in addition to high resolution data, supplementary

spectral information. The very high resolution satellite data have only four channels and thus it is impossible an adequate separation between buildings and background.

- ✓ For the achievement of very high accuracy in such procedures it is required the benefit of data that contain elevation information.
- ✓ The change detection accuracy by comparing independent classifications shows commitment to the accuracy of the individual classifications. Therefore, it is strongly suggested a very cautious selection of method according to the available tools. For example, in this study the simultaneous process of the two images in order to detect the changes proved much ineffective than the method that ultimately employed.
- ✓ The process of a whole satellite scene in Imagine Objective is not realistic. The main reason is the large amount of time required by the software to perform the procedures. In a method where the optimal solution occurs after experimentation with parameter values and observing their influence on the overall result, such disadvantage is prohibitive. To reduce the processing time to acceptable level is required very high computer performance, which in our case was not available. Therefore, splitting the image into subsets is strongly recommended.
- ✓ In software environments whose capabilities are maximized on the detection of only one class and that is general (e.g. buildings), one should separate the main class into individual classes with less spectral range and to create separate models for the feature extraction of each sub-class.
- ✓ In the present study, independent classifications were implemented in order to develop a unified building extraction model capable, with minor variations, to be applied to many images. This approach was sometimes at the expense of the final accuracy.
- ✓ To sum up, change detection on subsets of satellite scenes, with low geometric registration errors can be carried out successfully by Objective. If any of these conditions are not met, the accuracy will be reduced. Benefiting by elevation data can overcome the first and the third condition and using high computer performance the second.

5. References

[1] Ioannidis, C., Psaltis, C. and Potsiou, C., 2009. Towards a strategy for suburban informal building control through automatic change detection, *Computers, Environment and Urban Systems*, vol. 33, no. 1, pp. 64-74.

[2] Potsiou C., 2006. Informal settlements in Greece: The mystery of missing information and the difficulty of their integration into a legal frame work, in *5th FIG Regional Conference*, Accra, Ghana.

[3] Karavassili, M., 2004. Procedure Simplifications to facilitate application of urban planning and environmental legislation through control mechanisms amd inspections, in *Workshop on Urban Planning and Construction*, Athens, Greece.

[4] Mas, J. F., 1999. Monitoring land-cover changes: a comparison of change detection techniques, *International Journal of Remote Sensing*, vol. 20, no. 1, pp. 139-152.

[5] Bovolo, F. and Bruzzone, L., 2000. A multilevel parcel-based approach to change detection in very high resolution multitemporal iimages, *IEEE Transactions on geoscience and remote sensing*, vol. 38, no. 3, pp. 1171-1180.

[6] Singh, A., 1989. Digital change detection techniques using remotely-sensed data, *International Journal of Remote Sensing*, vol. 10, no. 6, pp. 989-1003.

[7] Imagine Objective Users Guide, Leica Geosystems, 2010.

[8] Jiang, N., Zhang, J. X., Li H. T. and Lin, X. G., 2008. *Semi-automatic building extraction from high resolution imagery based on segmentation*, in Earth Observation and Remote Sensing Applications, Beijing.

[9] Liu, Z., Cui, S. and Yan, Q., 2008. *Building extraction from high resolution satellite imagery based on multi-scale image segmentation and model matching*, in Earth Observation and Remote Sensing Applications, 2008. EORSA 2008. International Workshop on, Beijing.
[10] Ming, D., Luo, J. and Shen, Z., 2005. Features based parcel unit extraction from high resolution image, in *Geoscience and Remote Sensing Symposium*, *2005. IGARSS '05. Proceedings. 2005 IEEE International*, Seoul, Korea.
[11] Sahar, L., 2009. Using remote-sensing and GIS technology for automated building extraction.
[12] Volante, J. N., Campos, C. J., Noe, Y. E. and Herman, E. J., 2006. Metodo de clasificacion "Por-parcela" para la deteccion de cultivos: Applicacion al area agricola de las lajitas, Campana agricola de invierno 2006, Salta, Argentina.
[13] Michailidou, T., 2011. Automatic Change Detection Of Buildings In Suburban Areas From Very High Resolution Satellite Data Using Fuzzy Logic In Object Based Image Analysis, Ntua, Athens.
[14] Tsiggenopoulos, G., 2009. Automatic extraction of chartographic characteristics from satellite images, Ntua, Athens.
[15] Doucette, P., Agouris, P. and Stefanidis, A., 2004. *Automation and Digital Photogrammetric Workstations, Manual of Photogrammetry*, 5th Edition ed., C. McGlone, Ed., ASPRS.
[16] Wiedemann, C., Heipke, C., Mayer, H. and Hinz, S., 1998. Automatic Extraction and Evaluation of Road Networks from MOMS-2P Imagery, *International Archives of Photogrammetry and Remote Sensing*.
[17] Shan, J. and Lee, S., 2005. Quality of Building Extraction from IKONOS Imagery, *Journal of Surveying Engineering*.
[18] Mariano, V., Min, J., Park, J., Kasturi, R., Mihalcik, D., Li, H., Doermann, D. and Drayer, T., 2002. Performance evaluation of object detection algorithms, *Proceedings of International Conference on Pattern Recognition.*.
[19] Ozdemir, B., Aksoy, S., Eckert, S., Pesaresi, M. and Ehrlich, D., 2009. Performance measures for object detection evaluation, *Pattern Recognition Letters*, In Press.