

# DETECTING ROADS IN INFORMAL SETTLEMENTS SURROUNDING SAO PAULO CITY BY USING OBJECT-BASED CLASSIFICATION

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## ABSTRACT:

Uncontrolled sprawl occurring in large cities of developing countries requires intensive mapping efforts to update geodatabases. The intense urbanization process experienced since the 70's in Sao Paulo city illustrates this scenario. Despite aerial data and the more recent high resolution satellite imagery data which have been employed as the base for mapping, the need for precise, faster and cheaper mapping processes is real. Automated classification has demonstrated unsatisfactory results when traditional per-pixel classifiers are used. The increasing success of object-based classification has stimulated researches on creating new methodologies to provide geoinformation. The idea is extract object-primitives from images and use their information to compose strategies to improve the classification process. This paper reports this technology applied on road detection and classification in informal settlements areas. An 11 bit Ikonos multi-spectral image was used. Principal components were pre-computed and used on features customization. Auxiliary data were calculated from spectral information and combined with geometric information of the segments. Classification rules were created from objects information, by using combination between original multispectral bands, principal components as well as using combinations of geometric characteristics like width, length, neighbor and asymmetry and contextual ones. Considering the Ikonos second principal component as a good indicator of impervious areas, and considering the detection of bare soil areas, paved and unpaved roads were discriminated. Preliminary results have indicated that this classification method produces accurate results. Procedures and rules of the present methodology are presented here. Comparisons between automatic approaches and manual ones will attest the efficiency of the methodology.

## 1. INTRODUCTION

The Sao Paulo metropolitan region is composed by 35 municipalities, with a population estimated in 17 million people (Barros, 2004). The intense urbanization process experienced since the 70's has caused many problems concerning land use. Investigations of changes that are occurring on urban scenario are of extreme importance for land planning and land management. The uncontrolled sprawl that has occurred in large cities of developing countries presents an obstacle to urban management. (Nobrega et al, 2006). Traditional mapping efforts definitely could be the best technical solution, however they demand high effective cost due to the continuous emerging of buildings, roads as well as new settlements surrounding these cities. Nevertheless, the recent developments on Remote Sensing satellite and sensors include high recurrence time as well as improving in spatial, spectral and radiometric resolution, have stimulated new methodologies for land cover and land use classification. Precise monitoring and mapping locations on Earth's surface can be reached, including these new settlements surrounding large cities.

According Quintanilha & Silva (2005), on one hand, the large amount of details present at high spatial resolution imagery has created many possibilities in terms of offering geoinformation. On the other hand, the high internal variance of these images becomes a problem for traditional per-pixel classifiers. Considering that information present in a remote sensing scene are fractal in nature (Blaschke & Strobl, 2001), the more characteristics –geometric, spectral and topologic– for these objects, the more realistic the classification can be. The extraction of the object-primitives based on segmentation has supported the best results of classification for high resolution images. The object-primitives provide a

wide range of information to discriminate different land cover over in comparison to pixel attributes. Comparisons between traditional pixel-based and object-based methodologies have demonstrated the effectiveness of the new technology. Regarding the spectral analyses, the separability of urban features remains a challenge due to the large diversity their spectral patterns. Unknown spectral patterns, as well as the high heterogeneity of the urban environment require the combination between pixels and object information to effectively classifies the land cover as well as land use (Shackelford & Davis, 2003 ; Hoffman, 2001 ; Tso & Mather, 2001).

The goal of the present paper was to develop strategies for detecting and classifying roads in informal settlements by using object information extracted from high resolution satellite images. Rules must be created and adapted due to particularity of the land cover and land use. However roads are easy visualized from high resolution images, their automatic detection remains a hard task. Irregular patterns, different width and length, discontinuity and the high degree of spatial heterogeneity in terms of artificial and natural land cover can be considered challenges to automating the process, even for object-based classification.

Indeed, the results obtained here indicate a large potential to provide information about the unplanned urban sprawl from multi-spectral high resolution images. Considering the current demand for urban planning, these roads can be used as a layer of information on GIS efforts.

## 2. STUDY AREA, DATA AND TOOLS

The present research was developed near the urbanized extend of Sao Paulo city, in the southeast region of Brazil, close to the latitude 23° 27' S and longitude 46° 41' W. The

area is characterized by recent and unplanned occupation, where dense urbanization is found intermixed with preserved nature region. The preservation area composed by dense tropical forest and moderated to rugged terrain (see Figure 1) provides excellent conditions for water recharging and environmental balancing, which have been threatened due to excessive deforestation and uncontrolled land use.

The study area is located on the north part of the town, where informal settlements have removed the natural coverage, aggravating the environmental scenario. An increasing need to update land use/cover, conduct environmental impact assessments and map road networks, as reported in Repaka et al (2004) is found here. The region presents in detail the problem of unplanned sprawling out. A detailed description of the study area can be found in Barros (2004).

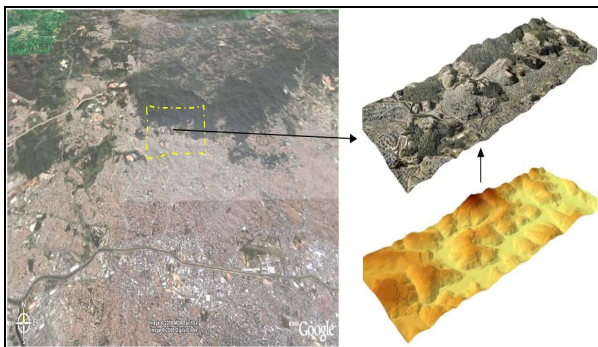


Figure 1. General visualization of north region of Sao Paulo (extracted from Google Earth) and the detailed study area.

An 11bit Ikonos image, recorded in 2002 over the north region of the town was used on this research. It is a CARTERRA Ortho Precision product compiled from a very precise Digital Terrain Model provided by local agencies for mapping. Also, the multi-spectral bands of Ortho Precision products are combined with the panchromatic one, resulting in a one meter resolution multi-spectral image, that are distributed by Space Imaging Corporate.

The methodology used here employed three software technologies:

- Erdas Imagine, to subset areas of interest and computing the principal components;
- Definiens eCognition, for the segmentation and object-based classification; and
- Esri ArcGIS, for mapping as well as comparative analysis

### 3. METHODOLOGY

#### 3.1 Overview

Supported by the use of information from object-primitives on modeling the classification scheme of roads on informal settlements, the methodology begins with processing of both segmentation and principal components. Upon generating the segments, information present on principal components also were used to create the strategies of classification. Although the goal is detecting and classifying roads, other features present on the scene must be considered. Auxiliary classes were created and their information helped to mine the roads. Creating local strategies was the goal of the research and it is presented on the next topics. The flowchart on Figure 2 describes a simple generalization of the classification scheme derived from the multi-spectral bands.

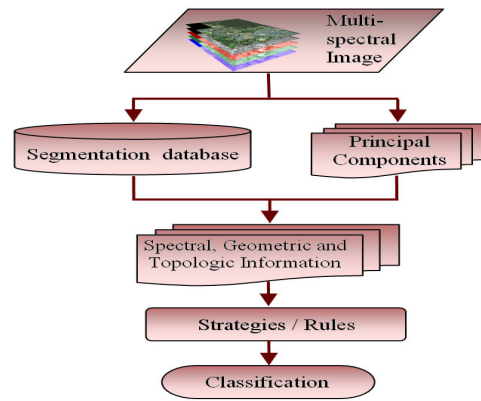


Figure 2. Scheme for object-oriented classification.

#### 3.2 Data Preparation

Objects extracted from image by segmentation, or supplied by databases, are the references for object-oriented classification. The more representative these objects, the more accurate the object-based classification. Criteria for pixel's homogeneity as well as for shape were previously established aiming the best fitting between the segments and the man-made features. Therefore, additional information were mined from these objects when new layers -principal components- were used.

**3.2.1 Segmentation:** Due to the importance of properties of the objects, the segmentation required extensive analyses to fit the desired urban objects relative to the segments. Variations of scale parameter, bands and shape and compactness criteria were previously tested until the features as streets, buildings, open spaces, shadows and urban-vegetation covered areas could be represented by the segments, as described in Freaman & Wolf (2005).

The four bands -NIR, Red, Green and Blue- were selected for the process, using the same weigh for all. Only one level of segmentation was used on the present methodology.

Unfortunately, the high spectral heterogeneity of dirty streets and roofs on study area reduced object separability and caused false objects when color criterion was increased on segmentation. Also, the strategies for road detection used here depend on geometric characteristics of the objects, which are enhanced by high shape and smoothness criteria, as described by Pinho et al (2005). By experimentation, the best result of segmentation was reached by using scale parameter 30, shape homogeneity 0.9 and compactness 0.1.

**3.2.2 Principal Components:** The high correlation of original bands sometimes produces intense computational efforts and generated inefficient results. The goal of principal components is minimize the number of linear combinations from the original data, but retaining as maximum as possible the information present on original data. Principal components were pre-calculated to provide a large range of spectral separability among objects presents in the scene. Moreover, the new mapping provided by principal components produces new ways to mine information of urban objects in remote sensing images.

The three first principal components were computed and employed in this research. Fortunately, both bare soil features and impervious surface features could be detected by using these new layers.

### 3.3 Mapping Impervious Areas

The goal for mapping the impervious areas was provide support for discriminating paved and unpaved roads. Principal components 2 as well as the objects created from segmentation were employed here. Considering these segments, mean values for pixels from principal components 2 were calculated. For Ikonos and similar multi-spectral images, principal component 2 can be a good indicator for identifying urbanized areas. The larger the principal components 2 mean value, the brighter the object. Auxiliary Data1 (illustrated in blue in Figure 3) was generated.

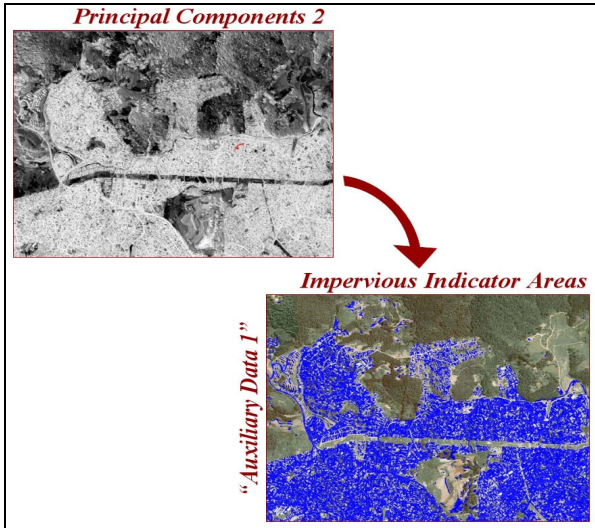


Figure 3. Principal Component 2 used as indicator of impervious surface areas.

### 3.4 Mapping Bare Soil Areas

Detecting bare soil areas also was necessary to discriminate paved and unpaved roads. Three features were customized and used to classify the land cover, applied to describe the three main classes: Vegetation General, Shadow General and Bare General, described in details in Nobrega et al (2006).

**3.4.1 Step 1 – Mask out vegetated areas:** NDVI (Normalized Difference Vegetation Index) was employed to detect vegetation covered areas. The NDVI computes the normalized difference of brightness values from NIR and Red rationing and its use is disseminated today. Indeed, the vegetated areas have higher values than others. Objects with NDVI value that are higher then the threshold of 0.2 were considered as vegetation and masked out.

$$NDVI = \left( \frac{\mu NIR - \mu Red}{\mu NIR + \mu Red} \right) \quad (1)$$

where:  $\mu NIR$  = mean value of NIR band per object;  
 $\mu Red$  = mean value of Red band per objects;

**3.4.2 Step 2 – Mask out shadow features:** The second customized feature was created to point out shadows and other extremely dark areas in the remaining image. The Shadow General Indicator uses a difference of brightness values between Blue band and the PC-1. Analyzing these two

images independently, the difference of brightness values for shadow and other similar objects are low in comparison with the remaining objects of the image. However in different ranges, the subtraction of PC-1 values from Blue ones produces a new map which negatives range. Highest values indicate the shadow objects that were detected and masked out. The threshold used was -425.

$$Shadow\_General\_Indicator = \mu Blue - \mu PC1 \quad (2)$$

where:  $\mu Blue$  = mean value of Blue band per object;  
 $\mu PC1$  = mean value of princ. comp. 1 per object;

These two initial steps were necessary due to the complexity of the scene. Both vegetation and shadow areas were masked out from the remaining classification scheme, increasing the ability to detect of bare soil objects.

**3.4.3 Step 3 – Detecting bare soil areas:** A combination of principal component 3 and blue band provide good reference for detecting bare soil features. Despite that principal component 3 could discriminate the bare soil objects, the excessive heterogeneity of study area increases the difficult to discriminate bare soil mixed with the buildings and the streets. Including blue band, a better separability was reached, due to the low brightness for bare soil areas and low variance in comparison with other bands.

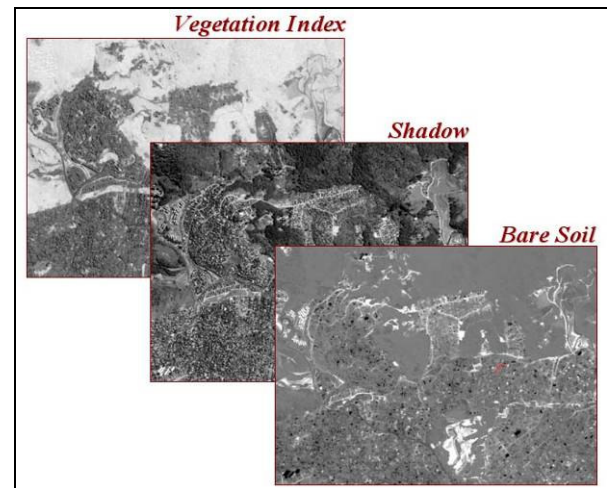


Figure 4. Scheme used for Nobrega et al (2006) to classify bare soil areas in informal settlements.

$$Bare\_General\_Indicator = \left( \frac{\mu PC3 * \mu Blue}{-100000} \right) \quad (3)$$

where:  $\mu PC3$  = mean value of princ. comp. 3 per object.

The large negative value of the denominator was introduced to generate value ranges equivalent to previous customized features. Again, by using the function *LARGER THAN*, and setting the inferior limit of the graph to 0.8 and the upper one to 1.0, higher values were classified as bare soil areas. The layers of information generated by each customized features can be seen on Figure 4. High values of NDVI correspond to bright areas of Vegetation Index. Dark features



of next image represent Shadow and the bright areas of third image correspond to open spaces. A sequential combination of these layers produced a map of bare soil areas.

### 3.5 Detecting Roads

Object-primitives (shape and context information) supported the detection of roads. The contextual land cover described before supported the classification for the detected roads. Then, the road detection was developed on sequential steps. As occurred on bare soil areas, vegetated areas previously detected from NDVI were masked out. The strategy was using partial information to step by step improve the capability to discriminate desired urban objects, as described by Skackelford & Davis (2003) and Ehlers et al (2006). Basically, the membership function employed asymmetry, length, width, rectangular fit, area as well as their relationships on road detection, presented on Figure 6.

In terms of geometric characteristics of features, especially man-made features present in urban areas, various factors must be considered to reach the best results on road extraction: the lengthier the image object, the more asymmetric it is, and is defined by the difference of semi-axis. Therefore, parameter such as length and width are computed by using a bounding box approximation surrounding each object. Area and border length are computed by the sum of elements. Combining these primitives can generate new information to be used for object-based classification. Also, additional geometric parameters can be obtained by using the skeleton of the features. A complete description of eCognition's tools can be found in Definiens (2004).

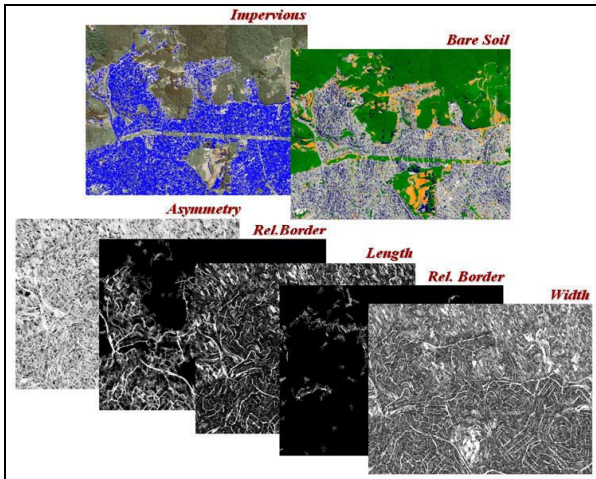


Figure 6. Some layers of information employed to detect and classify the roads by object-primitives and land cover.

Indeed, the shape proprieties supported the mining of unpaved roads from bare soil areas and paved roads from impervious areas. Moreover, these basic primitives extracted from shapes were employed to detect undesired urban features. Sometimes large buildings and parking lots were confused with streets. We minimized this problem creating filtering rules based on geometric proprieties. Topology, similarity between classes, class related feature and hierarchy from Definiens' eCognition also supported the filtering approach. Table 1 shows the basic object-primitives used during the detection and classification approaches.

Class	Membership Function	Limits	
Vegetation	NDVI	0.26 / 0.30	
	Shadow_Gen_Indic	300 / 400	
Shadow	Not Vegetation		
	Bare-General-Indicator	0.8 / 1	
Bare Soil	Not Shadow		
	Not Vegetaion		
Impervious	Principal Components 2	-350 / -320	
	Not Bare Soil		
Undesired Urban Features	Area	200 / 300	
	Asymmetry	0 / 0.5	
	Border to Impervious	1 / 2	
	Similarity to Impervious		
	OR		
	Brightness	1700 / 1800	
	Rectangular Fit	0.5 / 1	
	Impervious Child Class		
	OR		
	Brightness	1700 / 1800	
Trail	Rectangular Fit	0.5 / 1	
	Base Soil Child Class		
	Bare_General_Indicator	0.4 / 0.6	
	NDVI	0.1 / 0.11	
Unpaved Road	Rectangular Fit	0 / 1	
	Rel. Border to Vegetation	0.5 / 1	
	Border length	140 / 150	
	Length	25 / 50	
Paved Road	Length/Width	0.8 / 1	
	Not Paved Road		
	Similarity to Bare Soil		
	Not Large Building		
Paved Road	Border Length	140 / 150	
	Length	25 / 50	
	Length/Width	1 / 2	
	Similarity to Impervious		
	Not Undesired Urban Feature		

Table 1. Classes, membership functions and their values defined to extract and classify roads.

Contextual analyses were considered during the final steps. Unconnected objects previously classified as roads were disregarded, using criteria based on *relative border to* and *minimal area*. Once generated a map of road network, the visual results indicated excessive noise caused by undesired objects classified as roads, especially large buildings. To overcome this problem, an iterative filtering, based on geometric and contextual information was performed. However the final result looks cleaner in comparison with the previous result, several small roads were removed as well as gaps on existent roads were generated. On the other hand, some areas of roads were not classified and present gaps on the final map. The high degree of spectral and textural characteristics of the pixels that represent the streets, as well as the high variance of shape patterns caused this missing classification.

## 4. COMPARATIVE ANALYSIS

The accuracy assessment for the resulting classification was performed making use of reference map of roads. Comparisons between this reference map and the result of

classification could produce precise estimation of accuracy of the automatic approach. A quantitative analysis of common areas, mistaken classified features and features with missing classification was performed.

Unfortunately, the difficulties presented by the study area include the limited access to visit the suitable sites to collect ground samples. Also, considering roads as visible and recognizable features, and considering the monitoring of urban growth as a regular process supported by visual interpretation of aerial and satellite images, the reference map was manually produced based on the same images used in the classification, as shown on Figure 7.

Regarding the accuracy of Ikonos data and the cartographic generalization produced by classification process, the hands-up process considered the visualization scale of 1:2000 and the appropriated combination of Red, Green and Blue bands to minimize eventual errors. The digitized polygons were considered error-free.

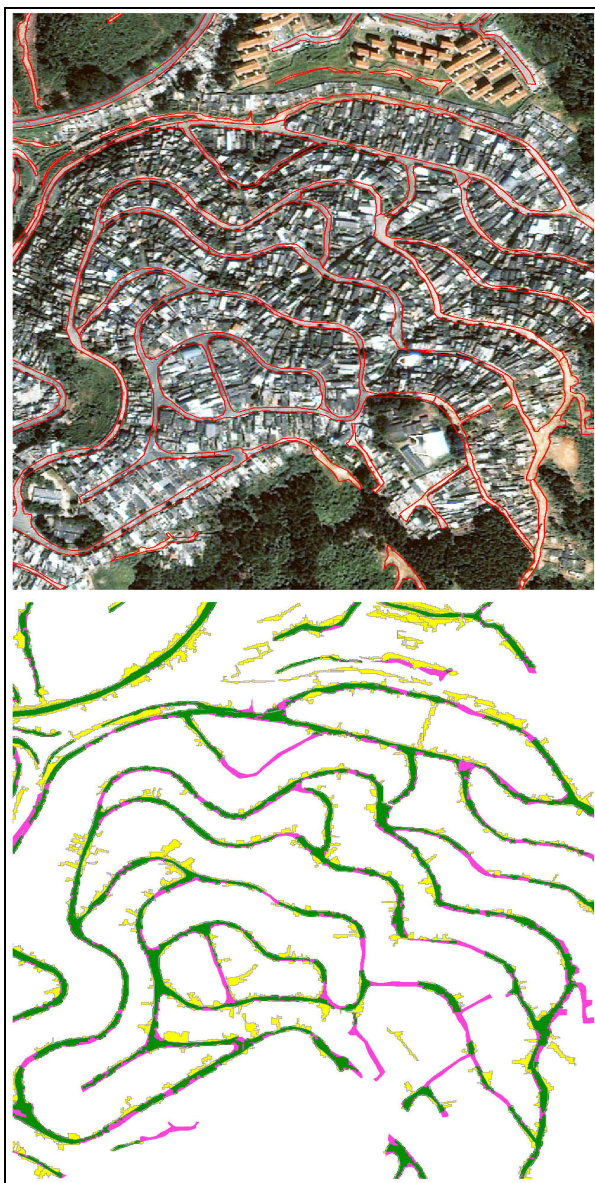


Figure 7. Upper, overlay of Ikonos image with reference polygons. Bottom, results of accuracy analysis. Correct classified areas in green, wrong classified areas in yellow and missing classification areas in pink.

Both reference road-network map and classification map of were introduced in a GIS system. Common intersected areas as well their differences generate the three layers employed for the analyses of the accuracy, as shown on Table 2.

Layer	Operation (?)
Correct Classification	Reference <b>INTERSECT</b> Classification
Missing Classification	Reference <b>ERASE</b> Classification
Wrong Classification	Classification <b>ERASE</b> Reference

Table 2. Layers employed on the analysis of accuracy.

## 5. RESULTS AND DISCUSSION

As result, a mask map containing of all polygons classified as roads was generate (Figure 8).

According to the objective proposed, the result was satisfactory, especially if consider the high degree of heterogeneity of the study area. The absence of considerable spectral, textural and geometric patterns to describe the features presents the most expressive challenge.

To evaluate the accuracy reached, a comparison between these two sets of road polygons was done. The overall accuracy was 65%. However object-based approaches have reached more precise results, we need to keep in mind that the roads in informal settlements are irregular, narrow and contain different pavements and textures. Sometimes their visual/manual photo-interpretation is also a hard task.



Figure 8. Ikonos reference image and the final roads mask map generate for whole study area.

Regarding the complementary error analysis, the omission error was 35% and the commission error was 72%. The most part of unclassified roads are composed by dirty over streets, trees, cars, buses and trucks. These undesired elements generated segments that disagreed with the strategies established. As commented before, the more intense problem regard to the excessive noise generated with the classification. Buildings and others man-made features sometimes agreed with the rules and caused the high degree of mistake on the classification.

However, one important parameter to be considerate for the classification accuracy is the cartographic scale. Setting the visualization scale for 1:5000, part of these noises is automatically eliminated. The appropriate scale for final analysis is one of the goals to be discussed on future works. Time processing was not computed in the present research.

## 6. CONCLUSIONS AND FUTURE WORKS

For the present research, two primary conditions were considered: the easiness of road detection in comparison of building detection from one-meter resolution imagery and the emersion of new roads as well as improvements on current ones as indicators for the urbanization process.

Since the goal of this study is present a methodology of detecting and classifying roads over informal settlements, some problems occurred regarding the characteristics of the study area. The extreme heterogeneity of the land cover associate with the small dimensions of the objects of interest presented a problem at least for high resolution images. It has forced different solutions combining land cover/use characteristics than present on publications applied for developed countries.

Regarding the comparative analysis, no samples were collected on the ground. A reference map of the roads was manually generated by visual interpretation using the same original data, reproducing the regular approach that has been performed to monitoring the urban growth. Comparisons between both automatic and manual classification for whole area produced a real estimation of the accuracy. Also, the errors associate with the classification –omission and commission- was evaluated.

Based on the difficulties presented as well as based on classification errors, the next steps include improvements for classification rules employing multi-layers of segmentation. An iterative approach involving sequential classification of objects of interest and objects surrounding them will be implemented. Vector lines, extracted from the skeleton of the final polygons and the centerlines of the reference street network will be analyzed together by using the Road Feature Evaluation Toolkit (Seo & O'Hara, 2004). It considers completeness, correctness, quality, redundancy distance statistics and gap statistics.

Apply the present methodology on different areas is also one of the future goals.

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