# OBJECT ORIENTED TRANSMISSION LINE CORRIDORS CLASSIFICATION USING LIDAR TECHNOLOGY AND A NON-METRIC DIGITAL CAMERA

*Classificação de Obstáculos sob a Faixa de Domínio de LT's Usando dados da Tecnologia LIDAR e Câmara Digital de Pequeno Formato mediante Análise Orientada a Objeto*

ANA PAULA BAUNGARTEN KERSTING
JORGE ANTONIO SILVA CENTENO

Programa de pós-graduação em Ciências Geodésicas
Universidade Federal do Paraná – Brasil
anakersting@gmail.com
centeno@ufpr.br

**ABSTRACT**

The increasing availability of high-resolution imagery as well as high density and accurate Digital Surface Models (DSMs) and Digital Terrain Models (DTMs) as provided by LIDAR (Light Detection And Ranging) technology, has been extending the use of remote sensing data in applications that demand a higher work scale, as transmission line design. The result of the processed LIDAR data consists in three-dimensional information about cables, structures as well as all obstacles along the corridor in a form of a point cloud with X,Y,Z coordinates and intensity value. Post-processing procedures are needed in order to discriminate features and to derive additional information. In order to discriminate the obstacles along the line corridor, information derived from LIDAR data as obstacles height and the intensity image, as well as color imagery from a non-metric digital camera are used. The integrated use of LIDAR data and color aerial photography provides more accurate classification result as well as the discrimination of additional features. The classification method used is based on an object-oriented analysis, which is considered the most adequate procedure when working with high-resolution imagery. In this work, the objects are generated using multiresolution segmentation, FNEA (Fractal Net Evolution Approach), hierarchical network of image objects, which represents image information in different spatial resolutions simultaneously. The classification method is based on fuzzy logic with the membership functions based on shape, texture, hierarchy and relation to neighbor objects. Transmission lines usually cross a variety of environments. The knowledge base constructed for urban areas is shown is this paper.

**RESUMO**

O aumento da disponibilidade de imagens de alta resolução espacial bem como a possibilidade de aquisição de informações precisas da altimetria dos objetos, como é o caso dos dados obtidos por meio da tecnologia LIDAR (Light Detection And Ranging), vem estendendo o uso dos dados obtidos através de técnicas de sensoriamento remoto a aplicações que exigem maior escala de trabalho, como é o caso de projetos de linhas de transmissão. O resultado obtido do processamento dos dados do sistema LIDAR consta de uma nuvem de pontos com coordenadas tridimensionais e intensidade de retorno do primeiro e do último pulso. Procedimentos de pós-processamento são necessários para a discriminação das feições e derivação de informações adicionais. Para a discriminação dos obstáculos sob a faixa de domínio de linhas de transmissão informações derivadas do LIDAR como altimetria e intensidade bem como ortofotos provenientes de uma câmara digital de pequeno formato foram usadas. O uso integrado de tais informações além de promover maior acurácia na classificação permite a extensão do conjunto de obstáculos passíveis de discriminação. Por se tratar de imagens de alta resolução espacial a análise orientada a objeto torna-se mais adequada. Neste trabalho, os objetos de análise foram gerados através da segmentação multiresolução, FNEA (Fractal Net Evolution Approach), que permite segmentar uma imagem em diferentes níveis hierárquicos inter-relacionados de objetos em diferentes escalas. A categorização dos objetos foi realizada por meio de classificador fuzzy, a partir da definição das funções de pertinência baseadas nos descritores de forma, textura e relação entre os objetos. Uma linha de transmissão percorre grandes extensões onde uma grande diversidade de alvos pode ocorrer. Neste trabalho é apresentada a base de conhecimento formulada em ambientes urbanos.

## 1. INTRODUCTION

Remote sensing, which is an important technique for the high-speed data acquisition about the earth surface, has made enormous progress over recent years. The increasing availability of high-resolution imagery, as well as high density and accurate altimetry data as provided by LIDAR technology, has been extending the use of remote sensing data in applications that demand a higher work scale, as transmission line design that recently has been done exclusively using traditional techniques.

During decades, traditional survey techniques have been used in transmission line design to collect terrain data for the up-rating of existing lines or design of new lines. The data collected along the centerline and side profiles has consisted in about 1 point every 10 meters. All obstacles, i. e., the land use/cover, that may influence the line design as vegetation, roads, rivers, crops, trees, buildings, other lines among others, should be mapped. The traditional technique, for requiring to physically occupy the survey area, ends up being time-consuming and expensive. High-density airborne LIDAR enables the collection of survey data for large areas, in short time frame and with high accuracy without problems of access restrictions and safety issues.

Although LIDAR is a powerful tool for collecting data of the earth surface, the collected raw data consists of a point cloud of x-y-z points inexplicitly describing the surface. It lacks differentiation between points measured on the terrain itself and points measured on man-made or natural objects. Post-processing procedures are needed in order to discriminate the obstacles. This work is intended to show the results of the classification of a transmission line corridor in an urban area using LIDAR data and color information from a non-metric digital camera. The simultaneous acquisition of image and elevation data offers the possibility to extract an increased number of features, and with that to improve the interpretation reliability from a statistical point of view (SHIEWE, 2003). The classification is accomplished using the object-oriented approach and classifier based on fuzzy systems available in Ecognition software.

## 2. BACKGROUND

The integration of LIDAR data with high-resolution imagery has been topic of research of several authors. HAALA and BRENNER (1999) combine multispectral imagery and laser altimeter data for the extraction of buildings, trees and grass-covered areas. ZENG et al. (2002) integrate IKONOS ortho-image and LIDAR data for an urban environment classification. For that purpose an hierarchical classification approach is employed. Altimetry data is used to separate the urban area into two parts: above the terrain surface and at the terrain level. The four bands of IKONOS imagery are used in the classification. Normalized vegetation index, computed by IKONOS red band and near infrared band is also imported into the classification in order to separate the vegetation objects from the non-vegetation objects. Maximum likelihood classification method is applied. TEO et al. (2004) present a scheme for building detection from LIDAR data and high resolution satellite imagery using region-based segmentation and object-based classification. WALTER (2005) integrates multispectral and LIDAR data for change detection and quality control in urban areas using object oriented classification.

According to BLASCHKE and HAY (2001) in order to fully exploit the information content of high-resolution images, methodologies are required which go beyond traditional statistical analysis and the classification of individual pixels. In particular, Blaschke and Strobl (2001) argue that classic per-pixel classification approaches do not explicitly make use of the spatial characteristics inherent within the image.

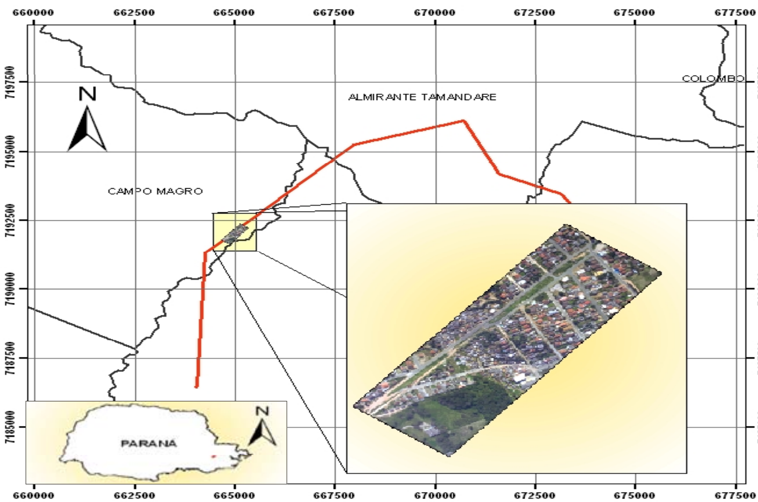
According to HUIPING et al. (2003) the high spatial resolution of advanced sensors increase the spectral within-field variability and therefore may decrease the classification accuracy of traditional methods on pixel basis (like the maximum-likelihood method). The reason is that classification clusters are built upon spectral homogeneities only. HOFFMAN (2001) argues that in contrast to classical pixel based image processing, the building blocks of object oriented image analysis are contiguous homogeneous image segments. These segments usually act as image objects. As such, they should ideally outline those objects of the real world, which are pictured in the image and are to be extracted (objects of interest). Once obtained, the description and in consequence the classification of the image objects can be performed by properties which lie far beyond the pure spectral information of the pixel's DN-values.

## 3. EXPERIMENTAL AREA AND DATASETS

### 3.1 Study Area

The study area comprises portion of the line *Campo Comprido - Pilarzinho* (230 kV) in Campo Magro city as shown in Fig. 1. This line belongs to COPEL - Company of Energy of Paraná State.

Figure 1. Study area



## 3.2 Data Acquisition

The data were collected by LACTEC (2005) using LIDAR sensor ALTM 2050 (Optech Inc.) and a non-metric digital camara Kodak DCS 14n. A survey flight aiming the acquisition of transmission line data should be planned in order to obtain adequate point spacing. Mission planning in terms of flight speed and height and aperture angle is set up to satisfy the necessary precision and resolution. The flight parameters of the collected data used in this work is presented in Table 1.

Table 1 – Flight Planning Parameters

| Flight Height (m) | Flight Speed (km/h) | Scan Angle (º) | Swath Width (m) | Pulse Repetition Rate (kHz) | Scan Rate (kHz) | Resolution (points/m) |
|---|---|---|---|---|---|---|
| 650 | 213 | 15 | 350 | 50 | 41 | 0,5 |

Once the data are collected, GPS data from the ground base stations and from the aircraft receivers are downloaded to compute by differential solution the high-accuracy kinematic post processed trajectory. The trajectory is then merged with the IMU data for a complete position and orientation solution. The laser ranging data are then merged, using geodetic algorithms, to the position and orientation to derive the end result, a X,Y,Z position for each pulse return measured by the sensor. In this work, first and last pulse data were available. Besides range measurements, the system used is capable of registering the intensity of the backscattered laser pulse (amplitude registration). Intensity is defined as the ratio of strength of reflected laser to that of emitted laser, and is influenced mainly by the reflectance of the reflecting object (SONG et al, 2002).

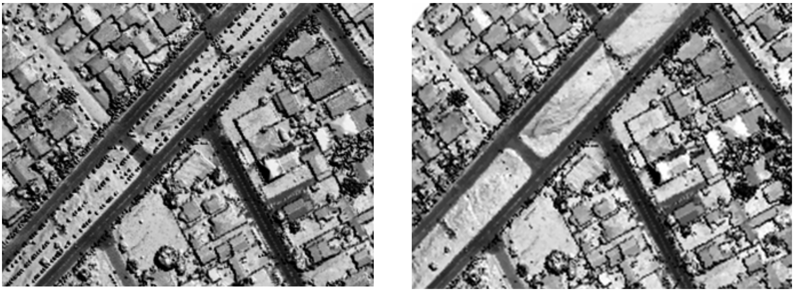
## 3.3 Pre-processing of the data for the Classification

### 3.3.1 LIDAR data

Previously to the classification, ground and wire points of the transmission line were classified using algorithms available in terrascan software (TERRASOLID, 2002). Next, the layers to be used in the classification were derived. For the analysis, the point cloud was resampled into a regular grid with the same cell size reached by the color imagery (12 cm). Information used in the classification process comprises:

- Intensity – Fig. 2a shows the intensity image generated using all points (first and last pulses) excluding just last pulses that are coincident with the first pulses. The image used in the classification was created excluding the points previously classified as wire of the line of study (Fig. 2b).

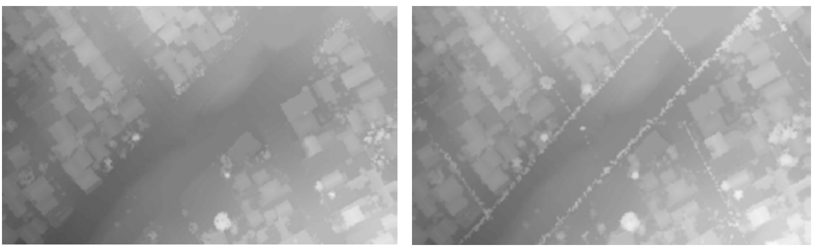
Figure 2. (a) Intensity image (b) Intensity image excluding wire points



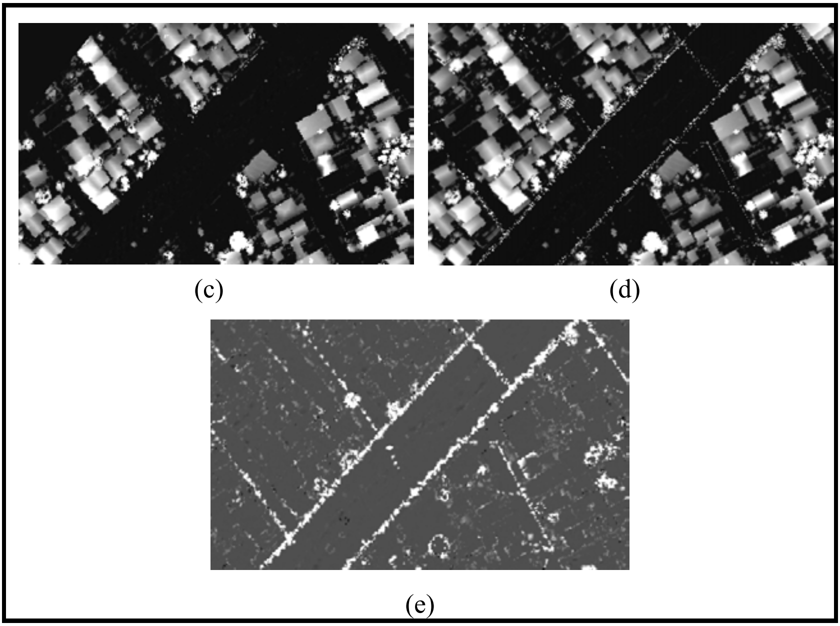
(a) (b)

- Digital Surface Model – This model was created using first and last pulses excluding last pulse when it is coincident with the first pulse.
- Digital Terrain Model – Model created using only the points previously classified as ground points.
- Normalized difference image – This image is generated by subtracting and normalizing first and last pulse images.
- Height derived from last pulse – Image created by subtracting the digital terrain model from the last pulse image (Fig. 3c).
- Height – Image created by subtracting digital surface model and digital terrain model (Fig. 3d).

Figure 3. (a) Last pulse (b) First pulse (c) Height derived from the last pulse (d) Height derived from last and first pulse (e) Normalized image difference



(a) (b)



3.3.2 Non-metric Digital Camera

As the camera used is not metric, it was calibrated using methodology described in ANDRADE (1998) and MITISHITA et al., (2001). In order to remove image distortions due to terrain relief and the perspective geometry, the image was orthorectified using the internal orientation parameter determined through the camera calibration and the digital surface model from LIDAR. As the position and orientation information from the GPS and the IMU is referred to the LIDAR sensor the exterior orientation parameters were refined through aero triangulation using bundle adjustment with the control points from the LIDAR intensity image The orthorectified image overlapped to the digital surface model can be visualized in Fig. 4.

Figure 4. Orthorectified image overlapped to the Digital Surface Model

## 4. CLASSIFICATION

### 4.1 Multi-resolution Segmentation

The first step in an object oriented analysis is the extraction of image objects by segmentation techniques. Segmentation is the subdivision of an image into separate regions based on discontinuity and similarity criteria (GONZALEZ and WOODS, 2000). Primitive objects are generated as a first approximation of the real world objects. The semantic representation is well represented in different scales. It is not always possible to extract objects with just one segmentation level which fits all classes in a classification schema. According to BLASHE and HAY (2001) the fractal net evolution approach incorporates an object-oriented framework and image segmentation techniques. In particular, it utilizes fuzzy set theory to extract the objects of interest, at the scale of interest, by segmenting images simultaneously at both fine and coarse scales, then building image semantics between levels and their elements. The principal challenge and flexibility of this multiscale approach lies in defining the aggregation rules for the lower level entities, which result in improved image classifications, and a new framework for integrating semantic rules in image processing.

The multi-resolution segmentation available in eCognition software is based on a heterogeneity criterion, see details in BAATZ and SHAPE (2000). The heterogeneity criterion consists of two parts: a criterion for tone and a criterion for shape. The tone criterion is the change in heterogeneity that occurs when merging two image objects as described by the change of the weighted standard deviation of the layer values used regarding their weights. The shape criterion is a value that describes the improvement of the shape with regard to two different models describing ideal shapes (DEFINIENS IMAGING, 2003). The balancing of these two criteria will depend on the nature of the information being extracted. The exclusive minimization of tone heterogeneity in general leads to branched segments or to image objects with a fractally shaped borderline. For this reason it is useful in most cases to mix the criterion for tone heterogeneity with a criterion for spatial heterogeneity, in order to reduce the deviation from a compact or smooth shape.

The study area was segmented in two levels. The first level of extracted objects, with a higher resolution, was used for the classification of the distribution lines. The other level, with a lower resolution, was generated for the extraction of the objects to be used in the classification of the remaining obstacles. In Table 1 are shown the layers and parameters used in the segmentation process.

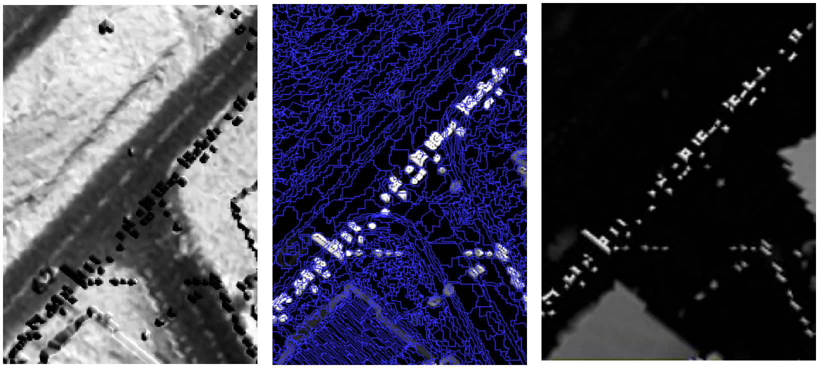
Table 2 – Layers and parameters used in the segmentation process

| Level | Scale Parameter | Layers | Weight | Shape Factor | Colour Factor |
|---|---|---|---|---|---|
| 1 | 15 | Intensity<br>Spectral Bands | 1<br>1 | 0.3 | 0.7 |
| 2 | 50 | Spectral Bands<br>Height | 1<br>0.8 | 0.3 | 0.7 |

The selection of the scale parameters was accomplished by several experiments. The ideal parameter would lead to segments with the same boundaries of the real world objects of interest. However, it was observed that with the increase of the scale parameter, the segments were being overestimated. Therefore the highest scale that would not lead to boundaries beyond the object of interest was tested.

In the segmentation process, different layers can be weighted as to their suitability for shaping the resulting image objects. In the segmentation of the distribution lines, carried out with the highest resolution, the intensity image and the color imagery were used. Although the distribution lines do not show contrast in the color bands, those layers were used to contribute to the subsequent super-objects generation, for the classification of the remaining objects. The result of the segmentation of the level 1, overlapped to the image of height (considering first and last pulse information) can be seen in Fig. 5.

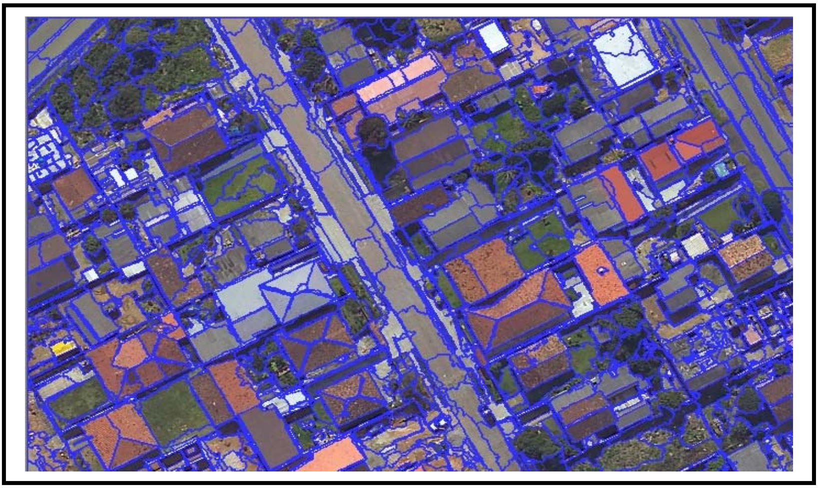
Figure 5. (a) Intensity image (b) Extracted segments level 1 (c) Height derived from first and last pulse



(a) (b) (c)

The second level (with lower resolution) was created using the color image from the non-metric digital camera and the objects height derived from the last pulse (generated by subtracting the digital terrain model from the last pulse image), once distribution line information does not appear in the last pulse data. Fig. 3c and 3d show height images derived from the last pulse and when first pulse data is also considered. A higher weight was given to the color information as it enables the discrimination of a larger number of obstacles. It could be observed that in almost all trees, the last return came from the crown, and others from branches or inferior leafs. As a consequence, in the segment domain of tree regions most of the objects had height when considering the last pulse information. That happened due to the flight configuration and the beam divergence used. The flight height of 650 m and a beam divergence of 0.2 mrad resulted in a footprint on the ground of 13 cm. The segmentation result can be visualized in Fig. 6.

Figure 6. Segmentation result of level 2



The image objects created are interconnected, in a way that each object has its neighborhood, making it possible the definition of dependency between objects. The hierarchical network is topologically definite, i.e., the border of a super-object is consistent with the borders of its sub-objects. Each level is generated based on its direct sub-objects, i.e., the sub-objects are merged into larger image objects on the next level. Merging is limited by the borders of super-objects; adjacent image objects cannot be merged when they are sub-objects of different super-objects.

## 4.2 Class Hierarchy

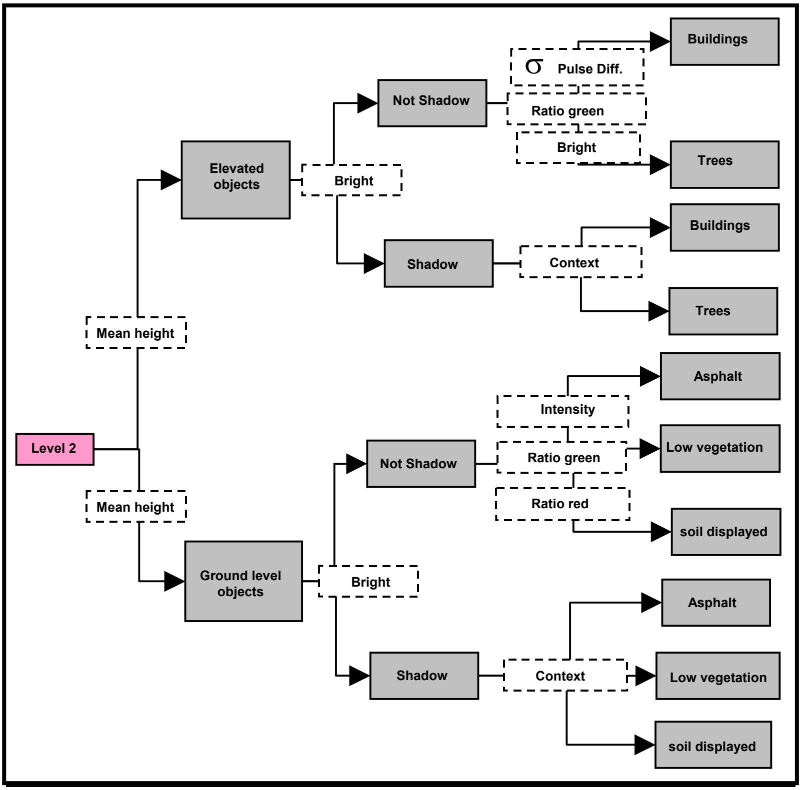
The class hierarchy is the frame for the formulation of the knowledge base for the classification of image objects. It contains all classes of a classification scheme in a hierarchically structured form. Different classes have different structure of attributes, however not always all attributes are different. When two or more classes have common attributes, a super class can be defined with a list containing the common attributes (MOLENARR, 1998).

Once the objects were created, the classes to be discriminated were defined in each level of objects. The classes were grouped in an hierarchy structure (Fig. 7). On the second level of objects (of lower resolution), the distinction of the objects which are on the ground level from the objects with height from ground, as trees and buildings, was first performed. For that purpose, a fuzzy membership function was defined considering the object's mean height derived from the last pulse. As distribution lines are not included in the last pulse data, in this level of segmentation high objects were classified as trees or buildings.

The class hierarchy defined, as well as the object features used to distinguish the classes in the segmentation level of lower resolution are shown in Fig. 7. Object features used were based on the layer values and class related features (context).

The lowest possible number of features was adopted to reduce the degree of complexity. The use of too many features in one class description causes an increase of overlaps in the feature space, complicates classification and reduces transparency significantly. The features used were defined by selecting several samples of the classes for the analysis of the separability efficiency of the classes, for each object feature.

Figure 7. Class hierarchy level




The discrimination of the objects in shadow areas was performed using brightness information. The tree and building classes were well distinguished using standard deviation of the pulse difference layer and brightness information. The pulse difference allows the classification of planar surfaces as building roofs, because last and first pulses are coincident. In tree regions, first return is reflected from the tree crown and last from the ground or inferior branches or leafs. They can be coincident sometimes; however in the domain of the segments created, first and last pulse returns will differ. The ratio of the green band was also used for providing better separability between the classes.

The objects above ground level (trees and buildings), in shadow areas, were classified using context information. This was done using neighborhood relations. If a shadow object has a high relative border to objects classified as trees, then the shadow object is considered to be a tree. For that purpose the relative area difference between neighboring trees and buildings were used.

The classification of the ground level objects, as asphalt, bare soil and grass was performed using the ratio (BAATZ et al., 2001) of the green channel, mean of the intensity channel and the ratio of the red channel. The object features used can be seen in Fig. 8.

Figure 8. Object features used for the classification of the ground level objects

**Color Image** **Feature**

**Ratio green channel**

**MeanInte nsity**

**Ratio red channel**

The class hierarchy created for the level 1 of image objects as well as the features used for the classification of the distribution lines are shown in Fig. 9. The objects above ground were classified using the height information, in this case created by subtracting the digital terrain model from the digital surface model. The digital surface model was created considering first and last pulse information, i. e., it includes points of the distribution lines. The classification of trees and buildings accomplished in level 2 were inherited by using the relations to super-objects: existence of trees and buildings. As we can observe in the partial classification result shown in Fig. 10, the remaining high objects includes not only distribution lines but also trees. As seen in Fig. 10, the objects in deciduous trees or trees with large gaps between branches, all the last returns were from the ground in the segment domain. As a consequence those objects did not take part of the level 2 classification process. In order to solve that the objects classified as trees, the remaining objects (which includes whole trees or portion of them), and the distribution lines were merged. The other objects were also merged (buildings and ground level objects). The class hierarchy created for this new level 2 (fusion) of super-objects is shown in Fig. 11. The objects would be classified as trees if in the super-object domain occurred sub-objects classified as trees. Then trees that were not totally classified, or trees belonging to a group of trees could be correctly classified as shown in Fig. 12. In the super-objects domain where no sub-object was classified as tree, the shape information, expressed through the object feature area, was used to distinguish trees from distribution lines.

Figure 9. Class hierarchy level 1

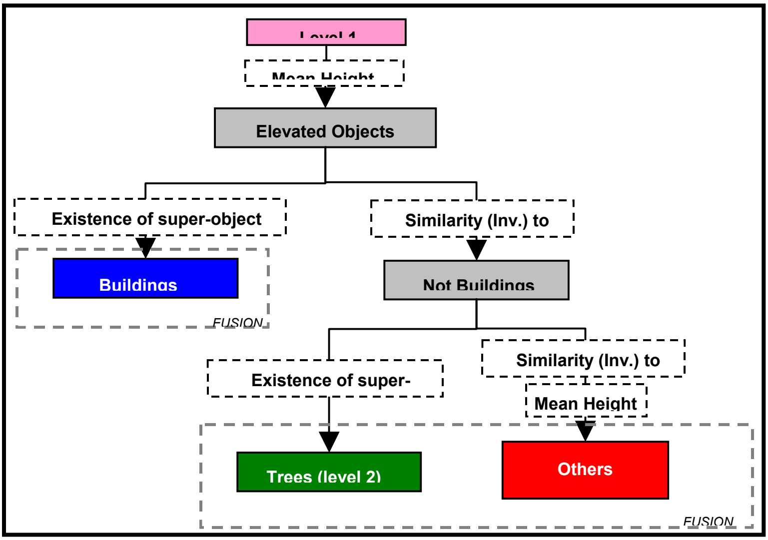


Figure 10. Partial classification result level 1

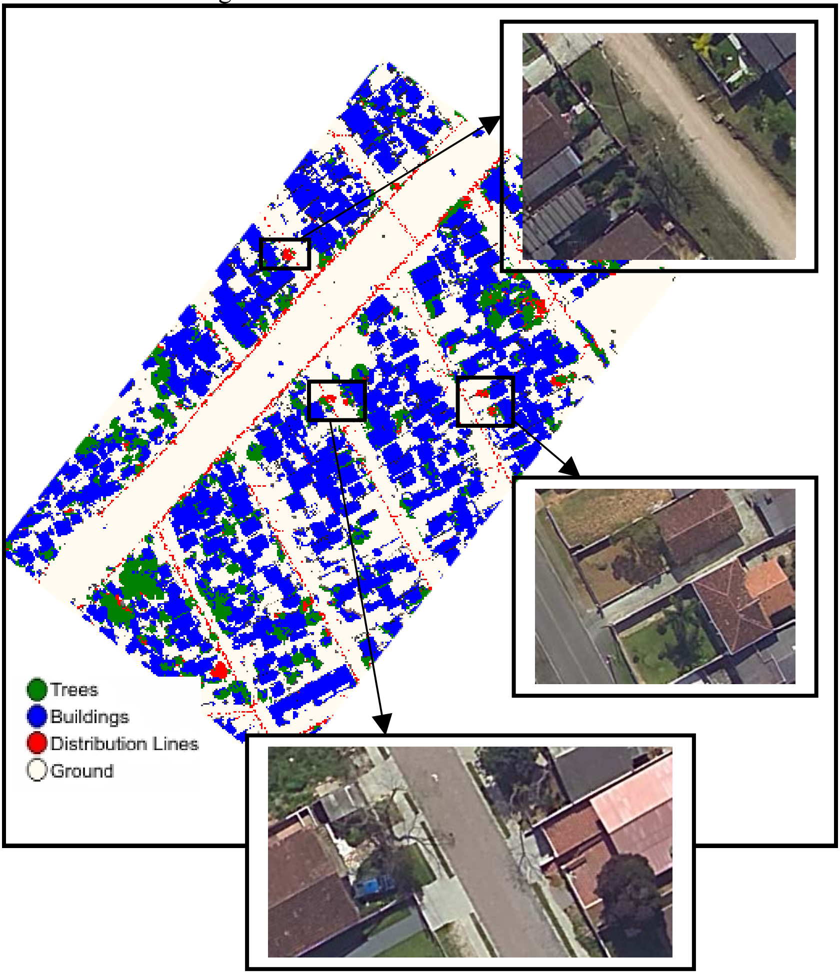


Figure 11. Class hierarchy level 2 (Fusion)

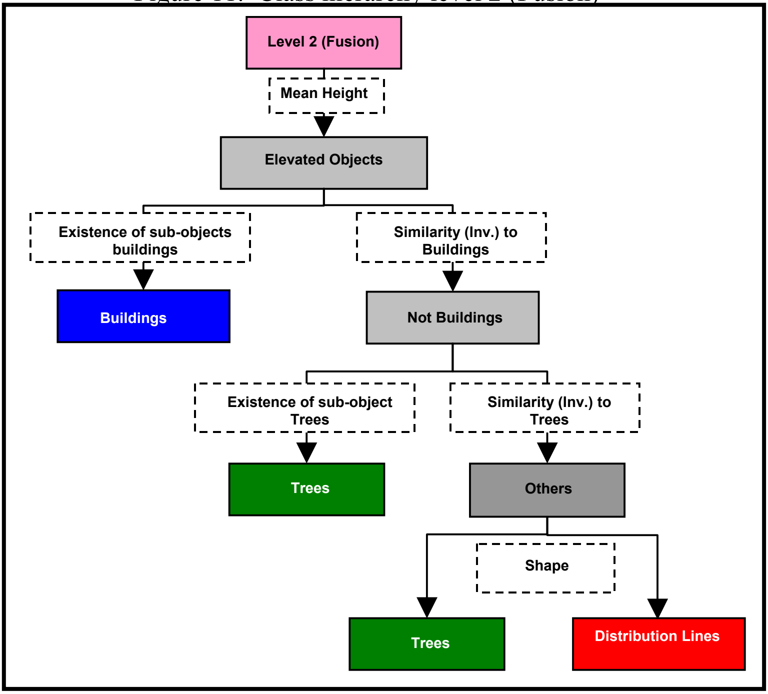
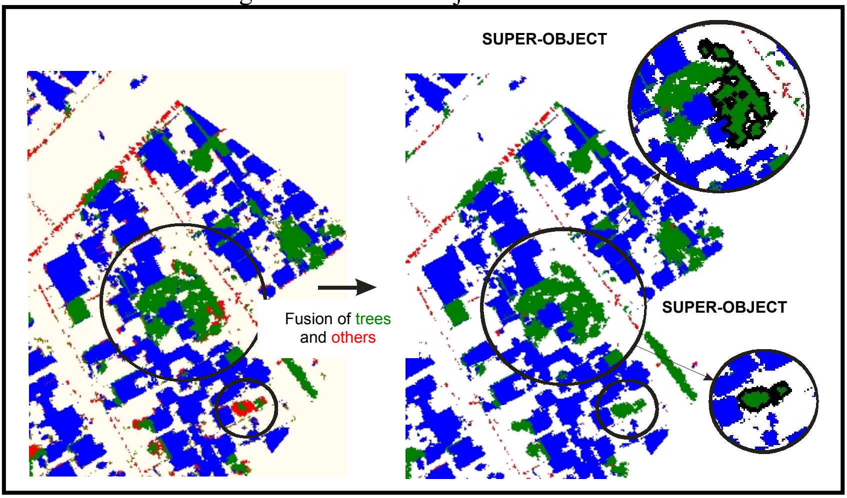



Figure 22. Level 1 objects fusion



### 4.3 Fuzzy Classification

Fuzzy logic is a multi-valued logic quantifying uncertain statements. The basic idea is to replace the two boolean logical statements ‘‘true’’ and ‘‘false’’ by the continuous range of [0,. . . ,1], where 0 means ‘‘false’’ and 1 means ‘‘true’’ and all values between 0 and 1 represent a transition between true and false (ZADEH, 1965). Avoiding arbitrary sharp thresholds, fuzzy logic is able to represent real world in its complexity much better than the simplifying boolean systems do. Fuzzy logic can model imprecise human thinking and can represent linguistic rules (BENZ et al, 2004). A class description for each class is formulated. It consists of a set of fuzzy expressions allowing the evaluation of specific features and their logical operation.

For successful classification a deliberate choice and parametrization of the membership function is crucial. The design is one of the most important steps to introduce expert knowledge into the system. Therefore, the better the knowledge about the real system is modeled by the membership functions, the better the classification result (CIVANLAR AND TRUSSEL, 1986).

Once constructed the segmentation levels, the class hierarchy and the membership functions based on the selected features were defined in Ecognition. For the classification of trees and buildings, a multidimensional membership function, generated through fuzzy approach of the nearest neighbor classifier, was used. Ground level objects were distinguished using one-dimensional membership functions combined through logical operators. Membership functions were created by analyzing the values distribution derived from several samples.

## 5. RESULTS AND DISCUSSION

When evaluating the quality of a fuzzy classification, besides classical methods of accuracy assessment, special methods based upon fuzzy concepts should be used. When using fuzzy classification methods, objects can belong to several classes but with different degrees of membership, which is the case when class descriptions overlap. Thus, to evaluate the reliability or stability of classes it is necessary to survey the different degrees of membership of the classified objects. A comparison between the best and second best membership values gives more evidence about the capability to separate the objects unambiguously. A simple operator, which expresses the relativity between two values, is their difference. The higher the membership’s difference, the more unambiguously an object belongs to its class.

The classification of the level 2 presented satisfactory results. To evaluate the classification accuracy a reference classification was defined by digitizing on the image considering all sources of information. The confusion matrix is shown in Table 3. Characteristic numbers that simplify the accuracy assessment of the classification (CONGALTON, 1991) are presented in Table 4.

Table 3 – Confusion matrix

| Confusion Matrix | | | | | |
|---|---|---|---|---|---|
| | **Buildings** | **Trees** | **Asphalt** | **Grass** | **Soil Displayed** |
| **Buildings** | 1569216 | 41370 | 0 | 0 | 0 |
| **Trees** | 61651 | 301664 | 0 | 1190 | 0 |
| **Asphalt** | 0 | 4641 | 713500 | 2287 | 8937 |
| **Grass** | 1227 | 0 | 14379 | 371302 | 0 |
| **Bare Soil** | 11263 | 0 | 43768 | 1794 | 360157 |
| **Not Classified** | 12614 | 17681 | 82500 | 17608 | 2324 |
| **Sum** | 1855971 | 365356 | 854147 | 394181 | 371418 |

Table 4 – Accuracy assessment

| Accuracy | | | | | |
|---|---|---|---|---|---|
| | **Buildings** | **Trees** | **Asphalt** | **Grass** | **Soil Displayed** |
| **Produtor** | 0.9476 | 0.8257 | 0.8353 | 0.9420 | 0.9697 |
| **Usuário** | 0.9743 | 0.8276 | 0.9782 | 0.9597 | 0.8637 |
| **Coef. Kappa por Classe** | 0.906 | 0.8063 | 0.794 | 0.935 | 0.9658 |
| **Acurácia Total** | **0.9107** | | | | |
| **Coef. Kappa** | **0.8757** | | | | |

Classification stability was analyzed through statistics derived from the difference between the best and second best membership values for each object. The results are shown in Table 5.

Table 5 – Classification stability

| Classification Stability | | | | | |
|---|---|---|---|---|---|
| | **Number of Objects** | **Mean** | **Std. Deviation** | **Minimum** | **Maximum** |
| **Buildings** | 2771 | 0.9543 | 0.1488 | 0 | 1 |
| **Bare Soil** | 1689 | 0.8602 | 0.2821 | 0 | 1 |
| **Trees** | 507 | 0.8581 | 0.2959 | 0 | 1 |
| **Grass** | 786 | 0.7478 | 0.3429 | 0 | 1 |
| **Asphalt** | 823 | 0.7424 | 0.4067 | 0 | 1 |

The classification of the level 2 (Fusion), aiming the discrimination of distribution lines, presented a global accuracy of 92%, showing satisfactory results.

## 6. CONCLUSIONS

This work presented a methodology for classifying transmission line corridors in urban environments through the integrated use of color information and altimetry data from LIDAR. The methodology developed was based on an object oriented analysis, consisting in multi-resolution segmentation for the extraction of image objects and the categorization of those segments by means of fuzzy classifier.

One issue that should be take into account in an integrated analysis of data from different sensors is the temporal and spatial coincidence. In this work, the digital camera and the LIDAR sensor were set up on the same plataform allowing the simultaneous acquisition. The spatial coincidence was achieved through the orthorectification of the color imagery. In this study, LIDAR data was not only used in the classification process but also for the geometric correction of the color imagery.

For the generation of appropriate object features in an image, in which objects of interest appear simultaneously in different scales, multi-resolution segmentation comes as an efficient tool for that purpose. Multi-resolution segmentation allows the extraction of image objects in different scales. The knowledge acquired in any level can be inherited by any other level.

Progress is expected in the methodology suggested for the detection of distribution lines. It is recommended the investigation of methods for the identification of straight lines in order to exclude points that do not belong to any line. This way the classification could be refined in a next step.

The results show the feasibility of the object-oriented approach for the classification of obstacle along transmission line corridor crossing urban environments. The integrated use of the data should be further investigated as well as the integration with other sources of data.

## REFERENCES


ANDRADE, J. B. *Fotogrametria* SBEE, Curitiba, 1998.

BAATZ, M. and SCHÄPE, A. *Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation*. 2000. München. Disponível em: http://www.definiens.com. Acesso em agosto de 2005.

BENZ, U.; HOFMANN, P.; WILLHAUCK, G.; LINGENFELDER, I. and HEYNEN, M. *Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information*. ISPRS Journal of Photogrammetry and Remote Sensing, v. 58, p.239-258. 2004.

BLASCHKE, T. and HAY G. J. *Object-oriented Image Analysis and Scale-space: Theory and Methods for Modeling and Evaluating Multiscale Landscape Structures*. 2001. Disponível em: http://www.definiens.com. Acesso em agosto de 2005.

BLASCHKE, T. and STROBL J. *What's wrong with pixels? Some recent developments interfacing remote sensing and GIS*. 2001. Disponível em: http://www.definiens.com. Acesso em agosto de 2005.

CIVANLAR, R. and TRUSSEL, H. *Constructing membership functions using statistical data*. IEEE Fuzzy Sets and Systems, v. 18, p. 1 –14. 1986.

CONGALTON, R.G. *A review of assessing the accuracy of classifications of remotely sensed data*. 1991. Disponível em: http://geology.isu.edu/BCAL/presentations/Mundt_2005_IMGIS_Accuracy.pdf. Acesso em outubro de 2005.

DEFINIENS IMAGING, *Ecognition User's Guide 3.0*. Disponível em: http://www.definiens.com. Acesso em maio de 2004.

GONZALEZ, R. and WOODS, R. *Processamento de imagens digitai***s**. Ed. Edgard Blucher, São Paulo, 2000.

HAALA, N. and BRENNER C. *Extraction of buildings and trees in urban environments*. ISPRS J. of Photogr. and Rem. Sens., v. 54, p. 130-137. 1999.

HOFMANN, P., *Detecting urban features from IKONOS data using an object-oriented approach*. 2001. Disponível em: http://www.definiens.com. Acesso em agosto de 2005.

HUIPING, H.; BINGFANG, W. & JINLONG, F. *Analysis to the relationship of classification accuracy segmentation scale image resolution*. In: Proceedings of IGARSS 2003 IEEE. Toulouse. 2003.

MITISHITA, E. A. and OLIVAS, M. A. A. *Calibração de câmaras aerofotogramétricas a partir de aerofotos digitais (Scanning)*. Boletim de

Ciências Geodésicas, Curso de Pós-Graduação em Ciências Geodésicas, UFPR, v. 7, n° 1, p. 64-76. 2001.

MOLENAAR, M. *An introduction to the theory of object modeling for GIS***.** Taylor&Francis, 1998.

SCHIEWE, J. *Multi-sensoral data processing for urban landscape modelling: New merits and new problems*. In: Carstens, J. (Ed.): Remote Sensing of Urban Areas, p.164-169. 2003.

SONG, J. H.; HAN, S. H.; YU, K. and KIM, Y. *Assessing the possibility of land-cover classification using lidar intensity data*. 2002. Disponível em: http://www.isprs.org/commission3/proceedings/papers/paper128.pdf. Acesso em novembro de 2004.

TEO, T. A. and CHEN L. C. *Object-based building detection from lidar data and high resolution satellite imagery*. 2004. Disponível em: http://definiens-imaging.com/documents/publications/PS-5-5.pdf. Acesso em maio de 2005.

TERRASOLID, *TerraScan user guide*. 2002.

ZADEH, L. *Fuzzy sets*. Inform. Contr. v. 8. 1965.

ZENG, Y.; ZHANG, J.; WANG G. & LIN, Z. *Urban land-use classification using integrated airborne laser scanning data and high resolution multi-spectral satellite imagery*. 2002. Disponível em: http://www.isprs.org/commission1/proceedings/paper/00100.pdf. Acesso em maio de 2005.

WALTER, V. *Object-based classification of integrated multispectral and Lidar data for change detection and quality control in urban areas*. 2005. Disponível em: http://definiens-imaging.com/documents/publications/PS-5-5.pdf. Acesso em maio de 2005.

(Recebido em novembro/2006. Aceito em março/2007)