Laser Scanning Data Segmentation in Urban Areas by a Bayesian Framework

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Key words: Conditional Autoregressive models, Bayesian approach, Digital Elevation Model, region segmentation, quad tree.

SUMMARY

In this paper is presented a region-based methodology for segmentation of Digital Elevation Model (DEM) obtained from laser scanning data. The methodology is based on two sequential techniques, i.e., a recursive splitting technique using the quad tree structure followed by a region merging technique using the Markov Random Field (MRF) model (Conditional Autoregressive model – CAR). The recursive splitting technique starts splitting the DEM into homogeneous regions. However, due to slight height differences in DEM, region fragmentation can be relatively high. In order to minimize the fragmentation, a region merging technique based on the Bayesian framework is applied to the previously segmented data. The resulting regions are firstly structured by using the neighborhood structure. Thus, two regions have connectivity between them if corresponding regions share a common boundary. Next it is used a hierarchical model, whose height values in the data depend on a general mean plus some random effect. Following the Bayesian paradigm, it was consider for the random effects a CAR prior. The posterior probability distribution was obtained by Gibbs sampler. Regions presenting high probability of similarity are merged. Experiments carried out with laser scanning data DEM showed that the methodology allows to obtain the objects in the DEM with a low amount of fragmentation.

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1. INTRODUCTION

Segmentation in computer vision and image analysis is the term used to denote the process of grouping parts of a generic image into homogeneous units with relation to one or several characteristics (or attributes), resulting in a segmented image (Ballard and Brown, 1982).

Feature segmentation is of fundamental importance in the context of spatial data capturing and updating for GIS (Geographic Information Systems) applications. Several image analysis techniques are used to segment the objects of interest, among them is the region segmentation. Region segmentation, depending on the purpose, can be defined as preprocessing for subsequent image analysis steps. In any case, in order to obtain the desired result, the object detection strategy must be efficient and reliable.

Substantial work on image segmentation has been developed to segment an image or a group of data to obtain high-level information on the regions or objects contained on the image to facilitate the interpretation of those objects. This stage is critical in some processes of image analysis. Some work has been done on segmentation using texture (Tuceryan and Jain, 1998), and others using color (Cheng et al. 2001). However, the combination of these two properties can supply more precise information to support the description of regions (Palm 2004).

In relation to airborne laser scanning technologies, some works can be quoted. In Lohmann (2002) and Voegtle and Steinle (2003) segmentation is performed on the point cloud and not in a raster image. Tóvári and Pfeifer (2005) present a combination of two approaches. The first works directly on the point clouds using geometric criteria to decide if a point is on the ground or an building. The second approach firstly segments the data and then make a classification based on segmented data. Schenk and Csatho (2002) describe a possible combination of aerial imagery and LIDAR data. Planar surface patches are extracted with region-growing segmentation. Possible adjacent planes are intersected while image edges are detected with a Canny operator. Some plane intersections are checked by merging edge information. McIntosh and Krupnik (2002) propose to detect (with an optimal zero-crossing operator) and match edges in aerial images to refine the digital surface model produced from airborne scanner data. Bretar and Roux (2005) present an approach for combining LIDAR data and aerial images. At first, LIDAR data are processed to extract building planar primitives. These primitives are inserted into a hybrid image segmentation algorithm based on a region-merging scheme.

In recent years the se of the Bayesian approach has attracted the attention of researchers from the image processing area. Applications involving the Markov Random Field (MRF) for image processing, such as segmentation and image restoration (Geman and Geman, 1984; Szirányi et al., 2000; Li, 2003) have been discussed thoroughly. However, MRF models have been recently used in high-level image analysis (Kim and Yang, 1995; Modestino and Zhang, 1992; Kopparapu and Desai, 2001; Andersen et al., 2002), for instance, image interpretation. Recently, the ISPRS (International Society for Photogrammetry and Remote Sensing) Commission III included MRF models as a reference term, whose main objective is to investigate applications in image analysis in Photogrammetry.

The main advantage of MRF is that it provides a general and natural model for the interaction among spatially related random variables on the image (Dubes e Jain 1989). The task of object segmentation in urban areas, due to scene complexity, requires the development of specific methods that integrate the neighborhood information and the domain knowledge of characteristics of the interest objects. Thus, this paper proposes a methodology for laser data segmentation in two stages. In the first stage, the recursive splitting technique based on the quad tree structure is used to accomplish initial DEM (Digital elevation Model) segmentation. A region merging technique using a Bayesian approach to improve the quality of the initial segmentation used in the sequence.

This paper is organized in four sections. Section 2 presents the methodology proposed for region segmentation, which is essentially based on a recursive splitting technique followed by a region merging technique using the Bayesian approach. Results and analysis are presented in the section 3. The conclusion and future perspectives are provided in Section 4.

2. DIGITAL ELEVATION MODEL (DEM) SEGMENTATION BY RECURSIVE SPLITTING AND BAYESIAN MERGING

We propose a methodology for laser data segmentation that is based on regular grid, i.e., a DEM. A recursive splitting and Bayesian region merging are sequentially used for DEM segmentation with a minimum fragmentation level. In other words, regions compatible with the objects on the scene are sought. Object recognition is not the objective of this methodology.

2.1 Methodology

Figure 1 shows the main stages of the proposed methodology.

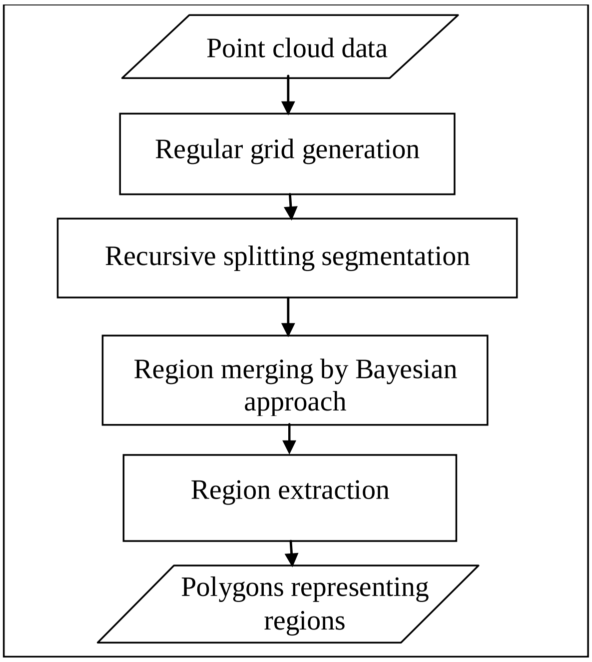


Figure 1 – Proposed methodology.

The laser scanner data are initially interpolated to generate a regular grid (DEM). After this stage, recursive splitting is performed using the quad tree structure. The recursive splitting technique consists of splitting the DEM into four homogeneous subregions of identical size. Each subregion is checked for homogeneity using a predefined threshold based on prior knowledge of objects presented in the scene. The splitting process proceeds recursively until no regions can be subdivided. In the end, the result is the input DEM organized according to the quad tree structure, where all homogeneous regions are explicitly represented.

In order to minimize the fragmentation, a region merging technique by CAR model is applied to the previously segmented data. After this stage, the regions can be extracted. A contour following algorithm was used for region contour extraction, followed by the recursive subdivision polygonization technique (Jain et al., 1995). Some additional details on recursive splitting and region merging are presented in the following sections.

2.2 Recursive Splitting using the Quad Tree Structure

The laser scanner point cloud consists of randomly distributed laser points. In this case it was necessary to interpolate the data to generate a regular grid (Morgan and Tempfli, 2000). A variety of interpolation methods exist in the related literature for DEM generation, including splines, finite elements, least squares, kriging, and nearest neighbor.

The method used was the nearest neighbor because it makes possible the preservation of the original height values on DEM, and it is computationally efficient.

A region in a DEM is a grouping of points with similar properties. DEM Subdivision into regions requires several decisions. However, the problem is in deciding which property to use in the subdivision. This question usually requires knowledge of the characteristics of the objects present in the scene. In that application, the variance of the height values is used as a measure of the dispersion of the values in a certain region. A technique used to split regions is the recursive region division, using the quad tree structure.

In the recursive splitting technique using the quad tree structure a region is split into subregions of identical size if the values of height variation in this region do not exceed a specified threshold. Each subregion is analyzed in relation to its homogeneity using a threshold based on knowledge of the objects present in the scene. The splitting process is repeated until there are no regions in the tree to be subdivided. The result is an organized DEM according to the quad tree structure, where all homogeneous regions are represented explicitly. Figure 2 shows an example of this technique, and more details can be found in Jain et al. (1995).

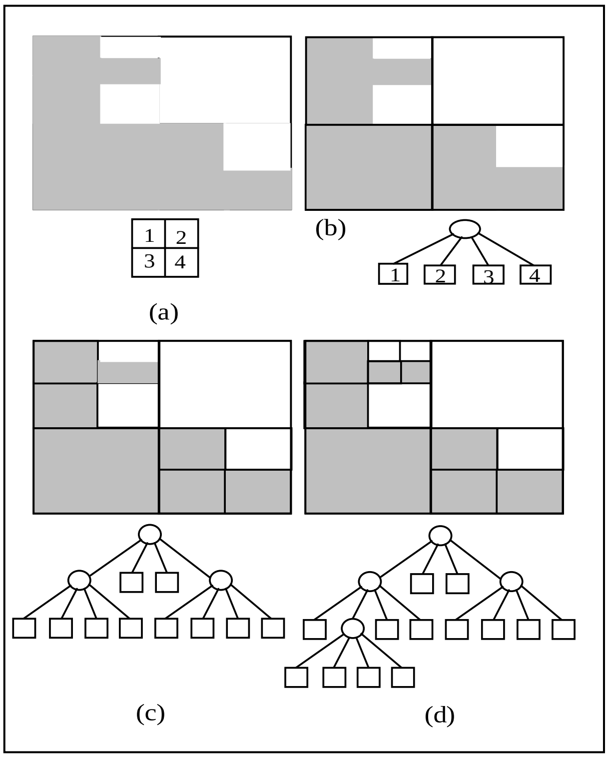


Figure 2 – The building of a quad tree. (a) Original Image. (b) Original splitting into four subregions (the left node in the tree corresponds to the top left region in the image). (c) Splitting the regions from (b) into four subregions. One of these regions is still a gray region. (d) Splitting of the last gray region and the final quad tree (Source: Adapted from Jain et al., 1995).

In this application, R represents the DEM, R_i is each DEM subregion and P a property (for example, the variance in heights of the points). This splitting is based on a hypothesis testing $H_0 : P(R_i) \leq \sigma_0^2 = \lambda$ (where λ is a prestablished value in agreement with the values of height of the scene objects) against the hypothesis $H_1 : P(R_i) > \sigma_0^2$. If $H_1 : P(R_i) > \sigma_0^2$, H_1 is accepted and H_0 is rejected. The segmentation of R is performed from successive subdivisions. Thus, if the H_1 hypothesis is accepted, then the DEM is split into smaller subregions. This technique generates a quad tree data structure, i.e., a tree in which each node is either a leaf node or has four children.

This approach can be summarized in the following stages:

1) Split the DEM into four regions.
2) For each region compute the variance of the height values.
3) If $P(R_i) > \sigma_0^2$, split the region into four subregions.

Whenever the H_1 hypothesis is accepted the second and the third stage should be recursively performed for all DEM regions. The process is concluded when the H_0 hypothesis is accepted for all regions. That means that the strategy should be performed recursively until there are no regions in the tree to be subdivided. Thus, the algorithm is concluded and a structure is generated. That structure corresponds to a segmented DEM, where each R_i is labeled with the mean height level of the corresponding region.

2.3 Region merging technique using the Bayesian approach

Let X be a segmented DEM over an $(m \times n)$ lattice defined on a regular grid $D = \{(i, j) : 1 \le i \le m \ \ and \ \ 1 \le j \le n\}$, where each region $X_{i,j}$ has a finite configuration of mean height. We assume that each $X_{i,j}$ is a realization of a normal random variable whose mean is modeled in function of a common factor (μ) plus random effects ($\varepsilon_{i,j}$), i.e.

$$X_{i,j} \sim Normal\left(\mu_{i,j}, \sigma^2\right) \qquad (1)$$

$$\mu_{i,j} = \mu + \varepsilon_{i,j}, \qquad (2)$$

Spatial dependence among observations is made assuming as prior distribution for the random effects $\varepsilon_{i,j}$ the CAR model, including the spatial dependence among observations. According to Schmidt, Nobre and Ferreira (2003) this distribution is defined as

$$\left(\varepsilon_i \mid \varepsilon_j \ \ j \ne i\right) \sim N\left(m_i, \upsilon_i\right), \qquad (3)$$

$$m_i = \frac{\sum_{j \in \delta_i} W_{ij} \varepsilon_j}{\sum_{j \in \delta_i} W_{ij}} \quad \text{e} \quad \upsilon_{\text{i}} = \frac{\upsilon^*}{\sum_{j \in \delta_i} W_{ij}}, \tag{4}$$

where δ_i represents the set of the neighboring regions to i. This specification results in the following joint probability distribution for ε ,

$$\left(\varepsilon \mid \upsilon^*\right) \propto \frac{1}{\upsilon^{*n}} \exp\left\{-\frac{1}{2\upsilon^{*n}} \sum_{i=1}^{n} \sum_{j<1} W_{ij} \left(\varepsilon_i - \varepsilon_j\right)^2\right\}. \tag{5}$$

The specification is complete when the neighbor matrix $W = [\, w_{ij}\,]$ and the prior distribution for variance υ^* are performed. In this case, we assume that $W_{ij} = 1$ if *i* shares boundaries with j and $W_{ij} = 0$, otherwise we then have

$$m_i = \frac{\sum_{j \in \delta_i} W_{ij} \varepsilon_j}{n_i} \quad \text{e} \quad \upsilon_{\text{i}} = \frac{\upsilon^*}{n_i}, \tag{6}$$

where n_i is the number of neighbors of the *i*th region and for υ^* we assume the Inverse

Gamma prior distribution (Schmidt, Nobre and Ferreira, 2003). Once the model and respective prior distributions were defined, the next stage is to obtain the posterior distributions. In order to get the region merging, the posterior distribution characteristics (e.g., maximum a *posteriori* – MAP estimate) for random effects are used. Simulated Annealing, Gibbs sampler and so on can be used for obtaining the posterior distributions (Geman and Geman, 1984).

3. RESULTS AND ANALYSIS

In this section the results of the proposed methodology using DEM by laser scanner data (figure 3) are presented. The threshold used in the recursive splitting was selected in accordance to the prior knowledge of the height variance in the scene. In the region merging stage, the Gibbs sampler implemented in the WinBUGS (Bayesian Analysis Using Gibbs Sampler) software was used to obtain the posterior distributions.

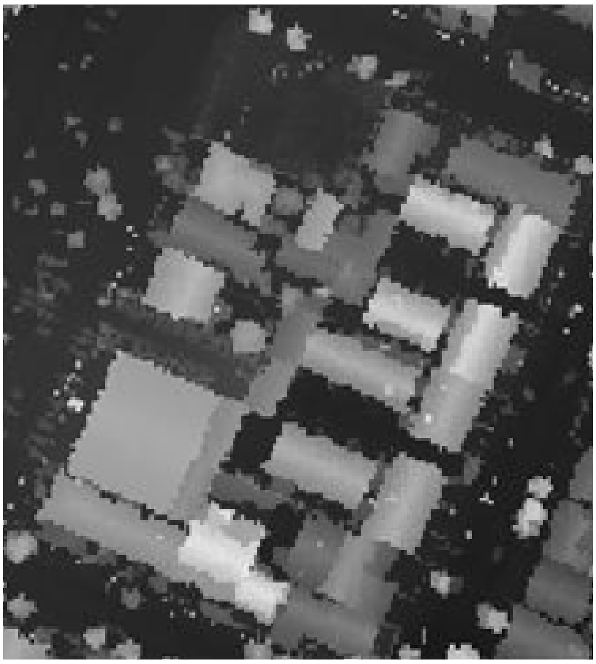


Figure 3 – Laser scanner DEM.

The region merging methodology is applied to the results generated by the recursive splitting technique. Figure 4 presents the results obtained with the Gibbs sampler algorithm. In this figure it is possible to observe the discrimination of objects existing in the urban block (figure 3) as e.g., roofs and trees. The regions in green represent the highest objects in the scene and the ones in other colors are associated with lower regions. The regions are classified in function of height estimates.

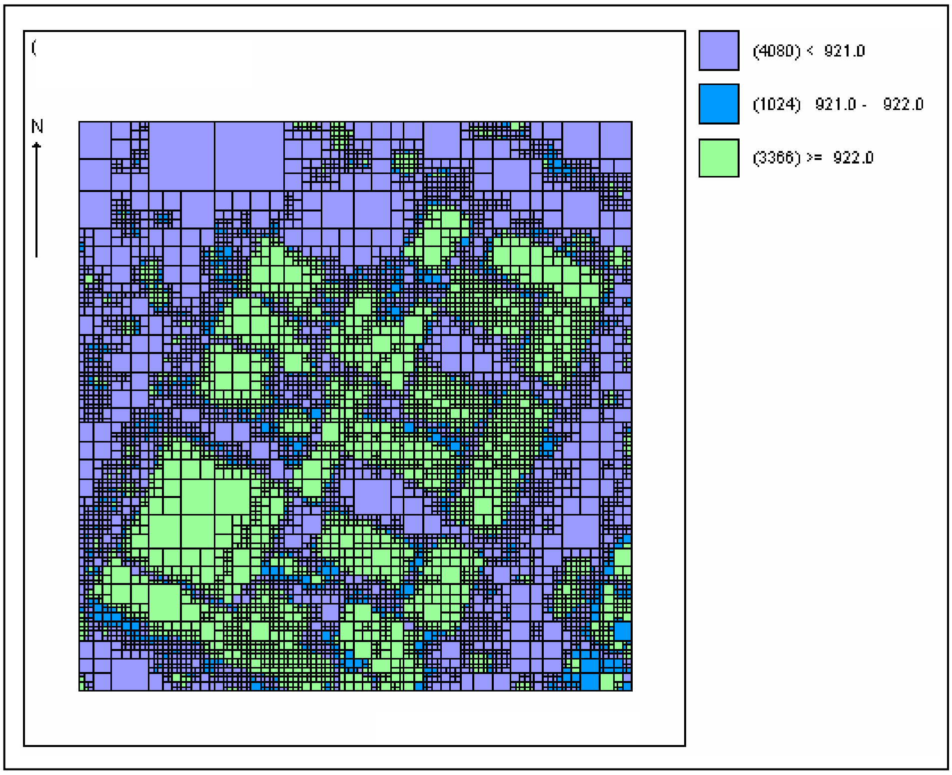
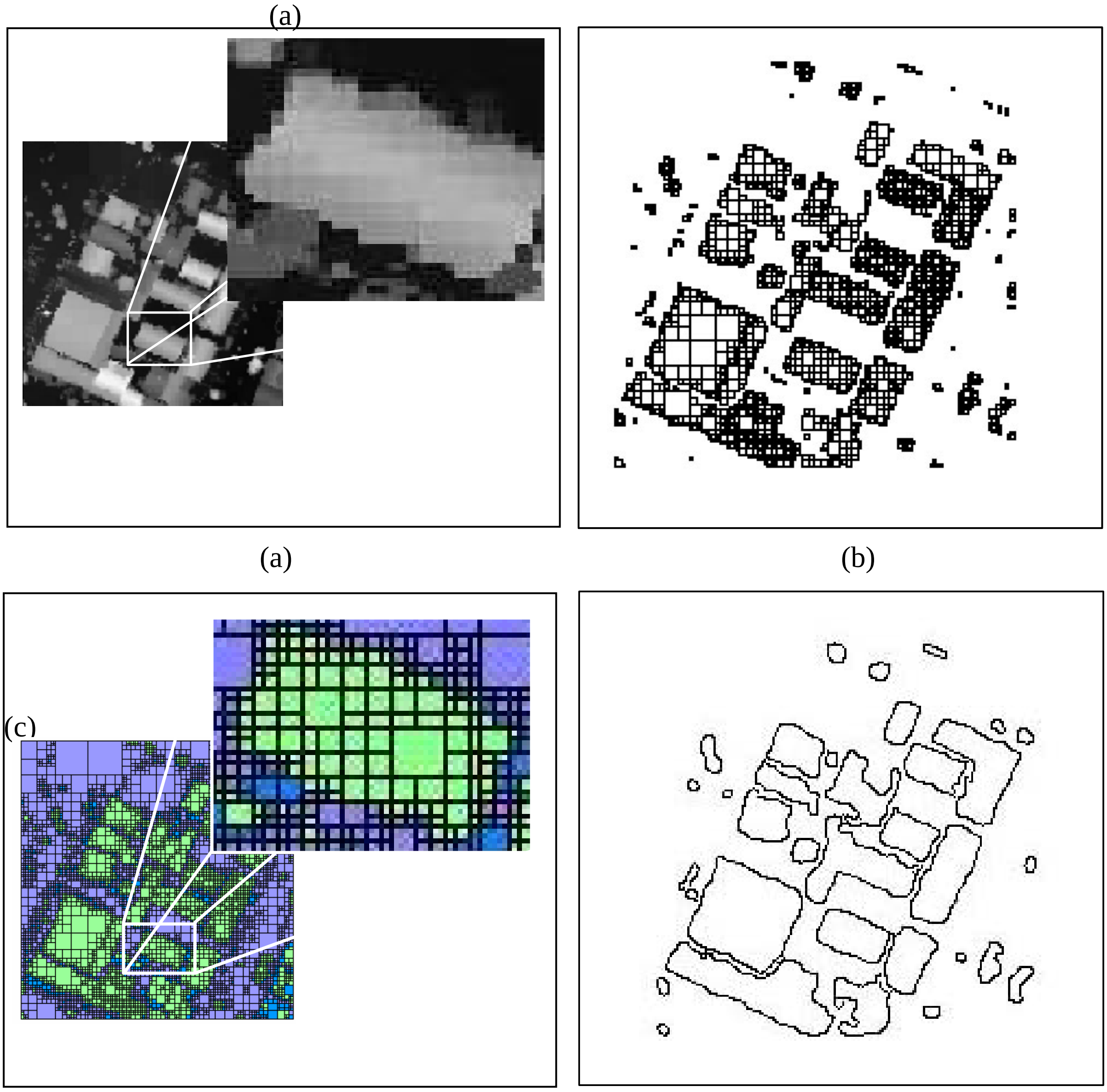


Figure 4. Results of region merging using the height estimates.

Figure 5 shows the result obtained with the recursive splitting process and with the region merging process. Figure 5(a) shows the result obtained by the recursive splitting process for a whole DEM, and for a small zoomed area. In this case the effect of the fragmentation resulting from the process of recursive splitting can be observed. Visually the differences among the color of the regions seem to be small but, however, the object (roof) is segmented in several subregions. The segmented DEM showed in figure 5(a) is vectorized and presented in figure 5(b). Although the figures 5(a) and 5(b) show an accentuated fragmentation of the objects, a distinction among subregion groups that compose the respective physical objects (for example, buildings, trees etc.) and the bottom region is evident. The Bayesian merging process seeks to find probabilistic similarities among predetected subregions, resulting in regions with high compatibility with the physical objects. Figure 5(c) shows, mainly in the window where the same object selected in figure 5(a) is highlighted, a significant improvement in the segmentation level. It can be noticed visually that now the quadrants corresponding to the object possess similar characteristics, that is, the same height. Figure 5(d) shows the final result, obtained by plotting the object contours in the segmented DEM by the proposed methodology. It can be stated that the object contours were usually extracted with good quality.



(a) (b)

Figure 5 – Result of the DEM segmentation using the proposed methodology. (a) Result of recursive splitting. (b)Contour obtained by the recursive splitting. (c) Region merging result (d) Contour obtained by region merging.

4. CONCLUSIONS AND FUTURE PERSPECTIVES

This paper presented the theoretical bases and experimental analysis regarding the process of region segmentation via recursive splitting with region merging using the MRF model. The steps in the process were described and an experiment was presented using a laser scanner DEM.

Bayesian modeling allows a data spatial structure by including a random effect into the model. Considering that this effect, representing specific characteristics of the objects in question, allows the incorporation in the analysis of the neighborhood relationship among regions, is obtained a model that represents the behavior of the phenomenon under study in a more realistic way.

The results obtained showed that the proposed strategy allowed the generation of regions closer to the physical objects, that include the highly desirable object (a roofs) and also undesirable objects, such as trees and vehicles. Among the objects detected, there can also be spurious ones, which result from DEM irregularities.

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