ROOF CONTOURS RECOGNITION USING LIDAR DATA AND MARKOV RANDOM FIELD MODEL ON GRAPH THEORY

Edinéia Aparecida dos Santos Galvanin
Mato Grosso State University, Mathematics Department
CEP: 78390-000 – Barra do Bugres - MT, Brasil
galvanin@gmail.com

Aluir Porfírio Dal Poz
São Paulo State University, Cartography Department
19060-900, Presidente Prudente, SP
aluir@fct.unesp.br

ABSTRACT

Building roof contour extraction methodologies is of fundamental importance in the context of spatial data capture and updating for GIS (Geographic Information Systems) applications. In this paper, a methodology is proposed for roof contour extraction from LiDAR data by Markov Random Field (MRF) model on a Graph theory. The motivation of this work is twofold: Firstly, the LiDAR technology has become common in recent years, this system allows the rapid and efficient acquisition of the Digital Elevation Models (DEM), with high precision and accuracy altimetry. Secondly, and more important in the scope of our research, 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. 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, and recently applications involving the MRF for image processing have been discussed thoroughly. 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. In this context, the proposed methodology comprises preprocessing steps: Initially is generated a DEM through the regularization of an available laser point cloud. High regions (buildings, trees etc.) are extracted from a DEM derived from Lidar data. The high object polygons are extracted by using techniques well-known, such as, recursive splitting technique by quadtree structure followed by a region merging, vectorization and polygonization techniques. In order to meet the goal, roof contour recognition, the building roof contours are identified among all high objects extracted previously. Using the available contours, a region adjacency graph (RAG) is constructed. Each node of the RAG corresponds to an image segment, and two nodes have connectivity between them if the corresponding two segments share a common boundary. Taking into account some roof properties and some feature measurements (e. g., area, rectangularity, and angles between principal axes of objects), an energy function is developed based on the MRF model. The problem of building roof contour automatic extraction is formulated as the Maximum a Posteriori (MAP) estimation, the solution of this function is a polygon set corresponding to building roof contours and is found by using a minimization technique, the Simulated Annealing (SA) algorithm. This algorithm guarantees convergence in probability to the set of globally minimal solutions. The proposed methodology was tested in an area with different object configuration complexities. The data area consists of a regular grid obtained by interpolated a LiDAR data set from Curitiba/PR city. Experiments carried out with LiDAR DEM´s showed that the methodology works properly, as it delivered roof contours with approximately 90% shape accuracy and no false positive was verified. The results with LiDAR data's DEM showed that the proposed methodology is promising allowing discriminate the urban objects in the scene. Based on an evaluation of the results, we discuss advantages and limitations of this approach.

INTRODUCTION

In the past few years the cartographic objects extraction has been receiving considerable attention. The LiDAR data have been common in cartographic extraction problem, the LiDAR data methodologies have been used in the most varied areas, but in the mapping are attractive the applications that involve the surface reconstruction and the objects extraction. That implicates in the solution of specific problems involving, for instance, segmentation and filtering of objects (buildings, vegetation etc.) (Haala & Brenner, 1999), generation of Digital Terrain Model (DTM) and Digital Surface Model (DSM) (Matikainen, Hyyppä & Hyyppä, 2005).

The methodologies for buildings roof extraction employing several strategies to achieve the desired goal. The theory of Markov random fields (MRF - Markov Random Field) have been the use in the cartographic objects extraction problem. The main advantage of MRF is that it provides a general and natural model for the interaction among spatially related random variables on the scene (Dubes & Jain 1989). According to Kinderman and Snell (1980) the MRF can be defined on Graph theory in image analyse.

The object segmentation task 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 automatic extraction of building roof contours using MRF on Graph Theory where its main advantage is provides a general and natural model for the interaction among spatially related random variables on the image.

This paper is organized in five sections. Section 2 is devoted to a brief introduction to Markov Random Field on Graph framework. Section 3 comprises the methodology. Results and analysis are presented in the section 4. The conclusion is provided in Section 5.

2 MRF ON GRAPH FRAMEWORK FOR IMAGE ANALYSIS

The MRF formulation for the image analysis problem can be realized as follow, using the segmented image, a region adjacency graph (RAG) is constructed. Each node of the RAG corresponds to an image region, and two nodes have connectivity between them if the corresponding two region share a common boundary. Next it is assumed that the node interpretation given the domain knowledge and the features obtained from the observed image obey a MRF model. Thus, the image analysis problem is solved as a MAP (Maximum a Posteriori) estimation problem. One of the great advantages of this approach is the possibility to model the knowledge contextual, that is, the relationship between the object of interest and the other presents in the scene.

2.1 MRF in Graph structure

According to Kopparapu and Desai (2001), the MRF formulation on graph structure consider a segmented image having n segments $\{R_1, R_2, ..., R_n\}$ and the corresponding RAG. Let $G = \{R, E\}$ be a RAG with nodes $R = \{R_1, R_2, ..., R_n\}$ representing the set of nodes R_i, $i = 1, 2, ..., n$ and E denoting the set of edges. There will be an edge between node R_i and R_j neighborhood system on $G = \{R, E\}$ be $\eta = \{\eta(R_1), \eta(R_2), ..., \eta(R_n)\}$, where $\eta(R_i)$, i = 1,...,n is the set of all nodes in R neighbors R_i. Note, $R_i \in \eta(R_j)$ if $R_j \in \eta(R_i)$.

A clique c, in this context, is a subset of the nodes of G (namely R) such that every pair of distinct nodes in c are neighbors. The set of all cliques of the graph G under the neighborhood η is represented with $C(G,\eta)$.

Now is defined the clique function V_{c_i} involving the nodes in the clique c_i. Thus, each cliques function, expresses the form and the degree of interaction (first order interaction, second order interaction etc.) that the node R_i has with its neighbors. In this context the $U(x)$ is referred to as the Gibbs energy function and is given by

$$U(x) = \sum_{c \in C(G,\eta)} V_c(x^c), \tag{1}$$

where $V_c(x^c)$ is the clique potential, and x^c is the value of the node variables for those nodes appearing in clique $c \in C(G,\eta)$. The Gibbs distribution, namely,

$$P[X = x] = \frac{1}{Z} \exp^{-U(x)} \tag{2}$$

where, x is a realization of X and Z is a normalization Constant commonly referred to as the partition function and is given by

$$Z = \sum_{toda\ conf.\ x} \exp^{-U(x)}, \tag{3}$$

$X = \{X_1, X_2, ..., X_n\}$ be the set of random variables defined on R. Each X_i corresponds to R_i. Moreover we assume that X_i takes values form a finite sample space. According to Kopparapu and Desai (2001) X is a MRF on G with respect to the neighborhood η if $P[X = x] > 0$ for all realizations of X; $P[X_i = x_i \mid X_j = x_j \quad \forall \quad j \neq i] = P[X_i = x_i \mid X_j = x_j \quad \forall j : R_j \in \eta(R_i)]$.

One of the advantages of a MRF model is that in general there exist a functional form for the probability distribution function, namely the Gibbs distribution according to Hammersley-Clifford theorem. According to Kinderman and Snell (1980), assuming that X has finite configurations over the sample space S, and that $P[X = x] > 0$, then X is a MRF with respect to a neighborhood η if and only if X is Gibbs distributed.

According to Modestino and Zhang (1992), due to the structure in the local and global properties are related through clique, the approach based on the model of MRF for image analysis supplies advantages in relation to the representation of the knowledge, learning and optimization.

3 ROOF CONTOURS RECOGNITION USING LIDAR DATA AND MARKOV RANDOM FIELD MODEL ON GRAPH THEORY

The proposed methodology comprises preprocessing steps: Initially is generated a DEM through the regularization of an available laser point cloud. High regions (buildings, trees etc.) are extracted from a DEM derived from LiDAR data. The high object polygons are extracted by using techniques well-known, such as, recursive splitting technique by quadtree structure followed by a region merging, vectorization and polygonization techniques (Jain, et al., 1995; Galvanin, et al., 2007). The section 3.1 present the methodology developed to separate the building roof contours, by MRF, among all high objects extracted previously.

3.1 Energy Function

Using the available contours, a region adjacency graph (RAG) is constructed. Each node of the RAG corresponds to an image segment, and two nodes have connectivity between them if the corresponding two segments share a common boundary. Taking into account some roof properties and some feature measurements (e. g., area, rectangularity, and angles between principal axes of objects), an energy function is developed based on the MRF model.

At this stage are calculated some attributes with basis in DEM. The analysis of each region, given the measures of some attributes taken in the regions of DEM, by hypothesis follows a MRF. Thus, the construction of the MRF involves the definition of appropriate functions and the analysis problem is solved from the MAP estimate. From the prior knowledge of the object of interest is possible to make the automatic extraction of roof contours. At this stage the proposed methodology involves the following steps: characterization of knowledge about contours of buildings, definition and minimization of the function of energy.

To define the clique, initially was assumed that the high objects $(R_i,\ i = 1,\ldots,n)$ immersed in a background F, are modeled as a MRF. The neighbourhood η_{R_i} i. e. from regions R_j neighbor of R_i $(i \neq j)$ is defined as,

$$\eta_{R_i,r} = \left\{R_j \mid dist\ \left(R_j,\ R_i\right) \leq r\right\} \tag{4}$$

where: the dist function is given by the Euclidean distance between the mass center of two objects analyzed$\left(R_i,\ R_j\right)$; and r is the maximum distance allowed between R_i and R_j.

The construction of the energy function $U(I \mid F,\kappa)$ depends substantially on a prior knowledge of the properties of the object roof. The prior knowledge about the object of interest denoted by κ is very important in the image analysis because requires a strong assumption about what is expected of the scene before applying the algorithm to perform the analysis. The characterization of κ imply to establish nominal values for the attributes that are considered important for decision in an analysis.

The features for the clique of first order used in this paper were the area and rectangularity. These features can be expressed mathematically according to geometric properties of the object. The area feature allows small object such as water boxes, whose area is relatively smaller in relation to roofs, can be discarded. To make this possible, the energy function should penalize small areas. For more detail on this features see example Modestino and Zhang (1992).

The third attribute is based on second order clique. As θ_{ij} the angle between the main directions of two objects $\left(R_i,\ R_j\right)$, sets up the following attribute of spatial relationships $\Phi(R_i,\ R_j) = sen(2\ \ \theta_{ij})$.

This attribute allows the verification of parallelism or perpendicularity between objects, because if $\theta_{i,\ j} = 0^\circ$ (objects with main axes parallel) or if $\theta_{i,\ j} = 90^\circ$ (objects with main axes perpendicular) $\Phi(R_i,\ R_j) = 0$. Therefore, in the knowledge κ must be assumed that the optimum value for this parameter is 0 (zero). This attribute favors the grouping of roofs, because the main axes of the roofs are parallel or perpendicular, which does not occur with other objects.

The objects analysis by MRF approach require energy function minimize. For the problem concerned, it is expected that for a specific DEM the solution is optimal, i.e., which is obtained from a setting of roof contour corresponding to the minimum value of the energy function. However, that optimal analysis depends on how of the energy function is defined.

The energy equation (Equation 5) was developed for the roof contour extraction, from high object contours previously extracted, as in (Galvanin, et al., 2007),

$$U = \alpha \sum_{i=1}^{n} (1- r_i) + \beta \sum_{i=1}^{n} \frac{(1-p_i)}{A_i} + \omega \sum_{i=1}^{n} \sum_{j \in (G,\eta)} p_i p_j \left| sen(2 \theta_{ij}) \right| + \gamma \sum_{i=1}^{n} \left[p_i \ln p_i + (1-p_i) \ln (1-p_i) \right] \quad (5)$$

where: α, β, ω and, γ are weight that gives relative importance to each term of energy function; r_i is the rectangularity measure of the object R_i, A_i is the object area R_i, p_i (or p_j) is an individual measure of compatibility, R_i (or R_j) with a roof contour, θ_{ij} is the angle between the main directions of objects R_i e R_j.

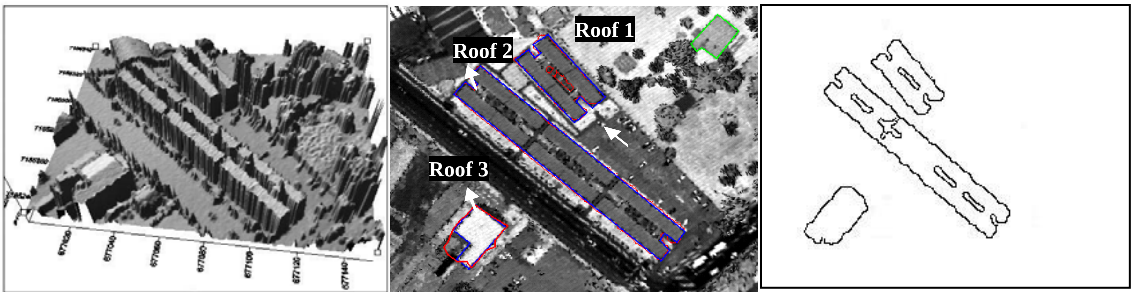
Minimize the energy function U (equation 5) implies minimize the four terms of U energy, simultaneous. At the end of the minimization process, i.e., when U is minimum, we have an optimal configuration of the contours that are buildings roofs. The final value p_i for the roof contours is one (1), while for the other object is zero (0). The simulated annealing optimization algorithm (SA) was used, which is effective in achieving the global minimum, even when the energy function has local minimal. As a comprehensive explanation of the algorithm SA require much space, more details see relevant references as (Kopparapu & Desai, 2001; Kirkpatrick, et al., 1983) .

4. RESULTS AND ANALYSIS

The test data consists of a DEM derived from LiDAR data. These data refer to an urban area of Curitiba (Brazil). The interpolation method by the nearest neighbor was preliminarily applied to these data to generate regular grid (MDE's) data with spacing of 70 cm between points in the grid. To perform this task the Surfer software was used. The analysis was done visually and numerically, based on comparisons between the results obtained with the extraction method and corresponding results obtained manually. The results of extraction and reference were numerically compared, consisting of obtaining the false positives percentages (extraction wrong), false negatives (not extract) and the buildings extraction rate proposed by Ruther, et al., (2002).

McKeown, et al., (2000) suggests that an overlap of 50% is appropriate to assume that the roof was detected. In this paper was used some thresholds, such as: for the energy function parameters was considered $\alpha = \beta = \gamma$ = 0,7 and ω = 0,99. These values were adopted with the aim of verifying the minimization of the energy function and behaviour of each term of energy function, respectively, in relation to obtaining the roof contour.

Figure 1 shows a three-dimensional visualization of the DEM regarding the test, where the high objects are easily identified. In total are 6 isolated buildings, and that 3 of them are aligned and practically linked, 2 others are isolated and the last is lesser building surrounded by vegetation. The final result are roof contours polygons in the DEM referential which are overlaid in red on the intensity image (Figure 1 (b)). This figure also shows the reference polygons (in blue) and a false negative (in green). Figure 1 (c) shows the representation of high object contours in polygons, and this result is beneficial in two aspects: the compactness and simplicity of the contours representation.



(a) (b) (c)

Figure 1 - Results of the roof contour extraction methodology of the test area. (a) three-dimensional visualization of the DEM. (b) Intensity image referring to the test area and final results overlapping. (c) High objects extracted contour.

It is possible verify by visual inspection of the results shown in Figure 1 that the biggest roof in the area test 1 (three buildings aligned) was merged in the preprocessing stage (Figure 1 (c)), resulting in a single roof contour. This fact occur probably because of the shadow (no data in the first laser pulse) in the cracks between those buildings, making the method of interpolation by the nearest neighbour fill those cracks close to roofs heights.

Figure 2(a) shows (in green) a building of a smaller size and mixed with the adjacent vegetation in this case was not possible in the preprocessing stage of the methodology to separate this building (see Figures 1 (b), 1 (c)). This shows that other strategies are needed to filter the vegetation before the second stage of the methodology.

The results was evaluated quantitatively, this experiment shows that the methodology had a good performance in the completeness of roof 1 (92%) and in the roof 2 (88%) and a regular performance in the roof 3 extraction (62%). An outline of roof was not extracted, resulting in a value of 25% for false negative. As there were no false positives, the building extraction rate reached the optimum value, i.e. 100%.

5. CONCLUSIONS

In this paper the experiments were conducted with real data, which provided subsidies for the performance analysis of the proposed methodology. The choice of test area took into account the complexity of the configurations of objects in the scene. Thus, were selected from test areas with roofs isolated until roof groups. The main goal of this choice was to verify the methodology robustness in different types of scene. In general, a good indication of robustness of the proposed methodology was the lack of false positives and the verification of few false negatives. The completeness parameters showed that the extracted polygons generally have high overlay with their polygons of reference.

REFERENCE

Dubes, R. C., Jain, A. K., 1989. Random Field Models in Image Analysis. Journal of applied Statistics**,** v**.** 16, n. 2, pp. 131–164.

Galvanin, E. A. S., Dal Poz, A. P., Souza, A. D. P., 2007. Segmentação de dados de perfilamento a laser em áreas urbanas utilizando uma abordagem bayesiana. Boletim de Ciências Geodésicas, v.13, pp.76/1 - 90.

Haala, N., Brenner, C., 1999. Extraction of buildings and trees in urban environments. ISPRS Journal of Photogrammetry e Remote Sensing, v.54, pp.130-137.

Jain, R. Kasturi, R & Schunck, B. G., 1995. Machine vision. MIT Press and McGraw-Hill, Inc New York.

Kinderman, R., Snell, J. L. 1980. Markov Random Fields and their applications. Providence, R.I: American Mathematical Society.

Kirkpatrick, S., Gelatt, C. D., Vecchi, M. P. 1983. Optimization by Simulated Annealing, Science, pp. 671–680.

Kopparapu, S. K., Desai, U. B. 2001. Bayesian approach to image interpretation. 127p.

Matikainen, L., Hyyppä J., Hyyppä H. 2005. Automatic detection of buildings from laser scanner data for map updating. In**:** ISPRS Workshop Laser Scanning, 2005. Proceedings.

Mckeown, D. M., Bulwinkle, T. M., Cochran, S., Harvey, W., Mcglone, C., Shufelt, J. A. 2000. Performance evaluation for automatic feature extraction. International Archives of Photogrammetry and Remote Sensing**,** v**.** 33, part B2, pp. 379– 394.

Modestino, J. A, Zhang, J. A. 1992. Markov Random Field model based approach to image interpretation. IEEE Transactions on Pattern Analysis and Machine Intelligence, v. 6, pp.606-615.

Rüther, H., Martine, H. M., Mtalo, E. G. 2002. Application of snakes and dynamic programming optimization technique in modeling of buildings in informal settlement areas. ISPRS Journal of Photogrammetry and Remote Sensing, v. 56, p. 269-282.

ACKNOWLEDGMENT

The authors thank the LACTEC that provided the data for this research (LACTEC from Curitiba - Brazil).