A New Graph-Based Approach for Urban Image Segmentation

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ABSTRACT

This article presents a new approach for graph-based image segmentation, applied to urban scenes of remote sensing data. Our method gets by input the results of a previous over-segmented image, from well-known algorithms like Region Growing, or Watershed. These input objects are connected in a structure called Region Adjacency Graph (RAG). By analyzing the connections, we look for rectangular shapes, *e.g.* rectangles, within connected nodes, since they are common in the urban environment. The objects, or graph vertices, whose union forms more rectangular shapes, are merged resulting in new and greater regions with shapes more adequate to the urban environment. We explain how to start from simple segments, applying a pre-processing and a pre-classification stage, to reach the final results by merging similar regions connected in the graph structure. Pre-classification stage performs unsupervised classification by Kohonen's self-organizing maps (SOM), clustering regions with similar classes. Similar regions are connected by RAG's and the algorithm searches for graph cuts, which increase the rectangularity of output regions. Some tests were performed, resultant accuracy and performance are analyzed and discussed. Also a free software for image segmentation is presented, so that community are able to evaluate it.

Keywords: Graph Based Segmentation, Re-Segmentation, Urban Imagery, Remote Sensing, Self Organizing Maps.

1 INTRODUCTION

Urban Remote Sensing images are becoming more and more precise with nowadays high resolution satellites. Data is constantly increasing, nevertheless the quality and precision of its analysis are also better. Several approaches for image segmentation have been already proposed in the literature [Lucc 01]. Some of them were applied to urban scenes, however they don't consider the shape of resultant objects.

From [Chen 06] we get a simple description of segmentation: "partitioning of a variable image into a subset of relatively homogeneous closed cells". Segmentation is also considered as an important first step of automated image analysis. Each region must have its own characteristics, such as spectral variability, shape, texture and context, distinguishing it from adjacent regions. Several algorithms consider only region's spectral features, and even texture. More sophisticated approaches deals also with context and multiscale segmentation. Our overture deals with shape features usually found at urban imagery.

Segmentation of urban scenes is still an open issue in the image processing area. In some cases, urban objects such as roofs and streets are segmented in small parts (Figure 1). Considering human perception, such regions do not have meaning without their neighbors.

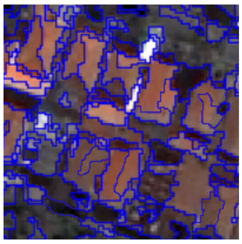

Figure 1: Urban scene segmentation – Roofs are over-segmented.

Spatial resolution increases the spectral variability and therefore may decrease the segmentation accuracy from traditional methods, *i.e.* based only on the image spectral features. And as high resolution imagery provides useful information on objects, novel and efficient analysis techniques are needed for efficient processing.

By seeing urban scenes, one can feel that through rectangular shapes, such as rectangles and circles, we can represent the complete structure of a street, for instance. Such objects, *e.g.* buildings, streets, trees, and roofs, ought to be rotated, or a combination from basic shapes. Nevertheless, it seems a challenging task to find these elements on images. In this paper we discuss some attributes from previously segmented objects and a graph, employed to produce better results from the re-segmentation.

This work aims to present a re-segmentation method, having as input one or more images and a set of regions

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obtained by previous segmentation. The methodology takes into account the shape and neighborhood of the urban objects, by the use of graphs, for merging them.

This paper is structured as follows. Section 2 presents a review of some graph-based segmentation methods, and some aspects on urban imagery. Succeeding, Section 3 starts explaining our proposed approach, called re-segmentation. We show some results at Section 4. On Section 5 we conclude.

2 LITERATURE REVIEW

We call our approach re-segmentation since it gets by input a previously over-segmented image, in general using traditional methods, such as watershed [Duar 06, Felz 04, Trem 00]. So, the input is composed by the image pixels and a set of regions, each one connected to its neighbors that succeed the topological operation "touch" [Egen 91]. Such connections are stored in an undirected graph, and the distance between nodes, also called weights, is defined as some difference of their attributes; generally spectral features, considering mean and variance.

Subsequently, a graph processing stage is performed, aiming to merge connected regions, when they are close to one another, according some attributes extracted from the candidate merged region. The graph is created in a structure called Region Adjacency Graph – RAG [Sche 93]. The way that nodes are joined, or not, is the main characteristic of every re-segmentation approach. We show and discuss our approach in Section 3.

2.1 Region Adjacency Graph

RAG's are a data structure which provides a spatial view of the image. One way to understand the RAG structure is to associate a vertex at each region and an edge at each pair of adjacent regions [Trem 00]. As already said, we get previous over-segmented regions from an image as input. Figure 2 shows a simple RAG in a synthetic image.

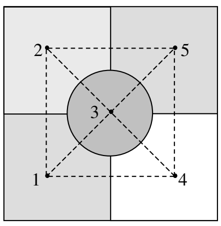


Figure 2: RAG example – simple regions and their connections.

The RAG can be covered, merged, and partitioned from several ways, considering the kind of results that we want to get. For example, [Trem 00] covers the graph and join a set of regions (or vertices) since their distance is small enough. In that case, the graph weights consider only the means of the regions.

Another approach [Duar 06], uses the so called hierarchical social metaheuristic for merging. This is based on human social behavior. First, regions are merged in a randomly way, forming a set of disjoint solutions, controlled by groups of objective functions. Iteratively, each group tries to improve its objective in a cooperative fashion, or competing with neighbor groups. This dichotomy between social cooperation and competition maximizes the quality of the results.

The work from [Lezo 03] applies a preprocessing stage, performing RAG smoothing on each region, and merging similar ones. This is iterated until the RAG satisfies some stop criterion, like the number of iterations or some similarity threshold is achieved. Using a nonlinear function, they perform smoothing over the iterations, considering spectral properties of a region and its connected neighbors.

Our re-segmentation approach is another way for merging nodes in the RAG structure. We aim to merge regions when they are similar considering spectral features (mean and variance) and the resultant shape is rectangular. As already said, we apply our approach to urban imagery, and such kind of image presents rectangular regions.

3 RE-SEGMENTATION THEORY

The theory is based on the RAG's construction. We build the graph considering topological relation "touch" between the regions. So, if two regions are connected, *i.e.* touch each other, they are candidate to be one node of the graph. However the regions must be closer in spectral features.

The proposed approach merges according a similarity measure based on shapes that better represent the urban environment. To accomplish such task, the input are splitted according urban classes present in the image (roads, buildings, trees, and roofs). The classification process is performed using the Self Organizing Map algorithm [Koho 01]. Such algorithm comprises the notion of a set of neurons, which through learning experiences, specialize in the identification of certain types of patterns. From each region, the algorithm extracts a set of shape and spectral attributes, such as perimeter/area relation, compacity and pixel means. This set of attributes is used to split the regions into their main classes. SOM algorithm also showed low computational cost when compared to other classification approaches, such as K-Means or Expectation Maximization.

Figure 3 shows the full re-segmentation diagram. The preprocessing stage is defined by the input patterns provided to the system. With each pattern, it is possible to make different inferences for merging regions. For rectangular regions, we aim to merge regions that result in greater objects with rectangular shapes. For other kinds of objects, which presents irrectangular shapes, we perform merging of similar regions, using spectral values. The process finishes when there are no more regions that can be merged.

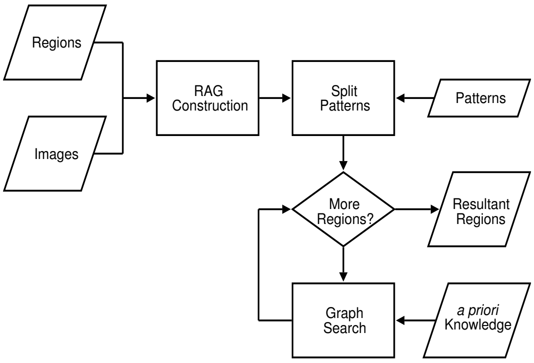


Figure 3: The re-segmentation diagram.

3.1 RAG construction

Let's consider an image I and a group of M regions, $P_i, i = 1, \ldots M$, and $\bigcup P_i = I$. We are building a graph, denoted by $G =< V, E >$, where $V = \{1, \ldots M\}$ is the set of nodes and $E \subset V \times V$ is the set of edges, or links between adjacent regions. In the graph notation, each region P_i correspond to one vertex, so $P_i = V_i, i = 1, \ldots M$.

As already said, each region is a vertex V_i. Adjacent regions will have the weights defined by some spectral differences. Table 1 contains the graph structure for example Figure 2. Here, just to show a simplified example, the weights are the mean differences between connected nodes. Weights with value -1 means no topological connection between nodes.

Table 1: Graph produced from Figure 2.

	1	2	3	4	5
1	0	20	30	30	-1
2	20	0	40	-1	20
3	30	40	0	60	30
4	30	-1	60	0	30
5	-1	20	30	30	0

3.2 Finding Rectangles

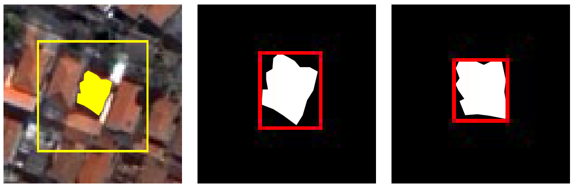
Our approach considers the shape of the input segmented objects, or regions. As already said, some classes found at urban images are rectangular, or similar to it. The main examples are roofs and streets. However, due to spectral features of images, the segmented objects often don't keep such rectangular shape, being separated in irrectangular objects. We aim to join such regions, when their union result in more rectangular shapes.

To detect up to which degree an object is rectangular, we can perform a relation between its area $AREA(P_i)$ and its bounding box area $AREA(BOX(P_i))$. Due to rotation, this value will not represent the rectangularity of an object. So, to make this attribute rotation invariant, we first rotate the object by its main angle. It is accomplished by principal components calculation.

Given an object P_i, and the coordinates of all points inside it $C = \{\{x, y\} | \{x, y\} \in P\}$, we get the covariance matrix of C. From the covariance matrix we get the eigenvectors. The first eigenvector's angle marks the main angle of P. So, by rotating the object, we create the new region R_i and its bounding box $BOX(R_i)$. From the areas of these new objects, R_i and its box, we can calculate an unbiased relation Q, as the following equation:

$$Q = \frac{AREA(R_i)}{AREA(BOX(R_i))} \qquad (1)$$

that results a value on the range [0, 1]. Such value approximates 1, the more rectangular is the original object P_i. Being more rectangular, we validate merging some instances of the RAG. An example of a rectangular object and the extracted parameter Q is shown at Figure 4.



(a) (b) (c)

Figure 4: Finding Rectangles: a) input region, b) detailed first region and its bounding box, and c) detailed rotated region and its new bounding box, with $Q \approx 1$.

At this stage, the algorithm is trying to find rectangles. We aim to look for nodes where a cut remains in more rectangular regions. Indeed we perform two types of cuts on each connected instances. The first cut is related to high spectral differences, resulting in weights above a user-defined threshold. It denies the algorithm to merge regions too different, such as shadows and buildings, for example. The second cut tries to split regions resulting in merges with $Q \approx 1$. This operation avoids, for instance, the generation of regions where two or more roofs become connected, such as in the example of Figure 5.

According to Figure 3, the algorithm takes some regions and generates a single one. This is achieved by merging the connected edges. However, our approach performs cuts into the graphs looking for regions with better rectangularity. Such operation is time-consuming, since it combines connected regions, and after the cuts, finds the most rectangular shape of the merged regions.

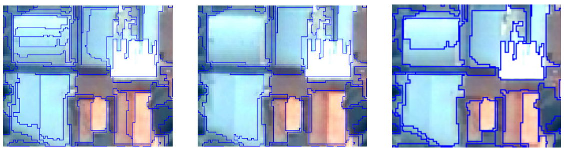
(a) (b)

Figure 5: Splitting Roofs: a) some connected regions, and b) correct re-segmentation, considering rectangular shapes.

4 FIRST RESULTS

This Section presents some results when applying our re-segmentation approach for urban imagery. We have a Quickbird scene from São José dos Campos city – Brazil, and some crops of the whole image showing some detailed results.

At first, a 300×250 image, is shown in Figure 6. We show the input over-segmented image, the resultant re-segmentation and a tradicional segmentation of the same image, for visual comparison. By observing the resultant re-segmentation on Figure 6b, we can perceive when the algorithm doesn't merge regions even spectrally close. They are connected in the graph, but because of the approach for re-segmentation, considering rectangular shapes, some regions are not merged, resulting in more accurate regions.



(a) (b) (c)

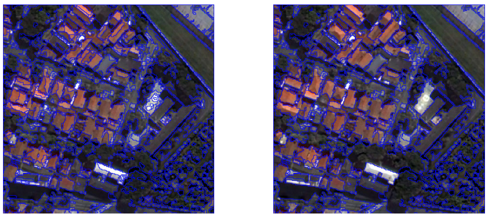
Figure 6: Complete re-segmentation cycle: a) input data, b) resultant merge, and c) tradicional segmentation for visual comparison.

The second result, a 256×256 image, is shown in Figure 7, where 7a is the input image and regions and 7b is the resultant re-segmentation. Such Figure contains several instances of roofs, that on ordinary segmentation methods (such as Figure 6a) become separated as different regions. As already said, the segmentation is the key step for further image analysis. Using our approach, posterior stages on image recognition, concerning the meaning of the segmented objects, can become more accurate, since our results comprise the notion of objects, instead of a simple group of pixels with spectral similarity.

5 CONCLUSIONS

A description of our approach for image re-segmentation was presented. Some of the implementation were discussed and results for certifying the method were also shown. The main contribution of this paper was the new way for finding rectangular regions in urban imagery. Other segmentation methods, applied to the urban case don't consider the shape of the objects. In such a way, we can get better results by using *a priori* knowledge and the search for rectangular objects, when dealing with roofs or streets, for instance.

The algorithm has been developed in the Free C++ Library called TerraLib [Cama 00], available for free download at `http://www.terralib.org/`. The full application for urban image re-segmentation will also be available at the same URL, considering related projects.



(a) (b)

Figure 7: Second re-segmentation result: a) input data, and b) resultant merge.

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