Image Re-segmentation: A New Approach for Urban Imagery

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IMAGE RE-SEGMENTATION
A New Approach Applied to Urban Imagery

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Abstract: This article presents a new approach for image segmentation applied to urban imagery. The proposed method is called re-segmentation because it uses a previous over-segmented image as input to generate a new set of objects more adequate to the application of interest. For urban objects such as roofs, building and roads, the algorithm tries to generate rectangular objects by merging and cutting operations in a weighted Region Adjacency Graph. Objects whose union generate larger regular objects are merged or otherwise cut. In order to verify the potential of the method, two experimental results using Quickbird images are presented.

1 INTRODUCTION

Segmentation is an important operation in various image processing and computer vision applications, since it represents the first step of low-level processing of an image. Many approaches have been proposed in the literature (Lucchese and Mitra, 2001). However, just some of them have been applied to urban scenes, although most of them do not take into account the object shape information.

(Chen et al., 2006) define segmentation as *partitioning of an image into a subset of fairly homogeneous closed cells*. Here we refer to "closed cells" as regions or objects. Each region must have its own characteristics such as spectral variability, shape, texture, and context, which can be distinguished from its adjacent neighbors. Several algorithms use mainly the region spectral properties to segment an image. More elaborated approaches also deal with contextual and multiscale segmentation (Baatz and Schäpe, 2000).

The details in a high resolution image holds its spectral variability and may decrease the segmentation accuracy when traditional segmentation methods are used. In urban scenes, one can observe that regular shapes such as rectangles can efficiently represent the structure of a street, or a roof, for instance.

Therefore, this paper aims to present a novel approach for high resolution image segmentation. The proposed methodology takes into account shape attributes besides the spectral ones to produce more accurate segmentation.

This paper is organized as follows. Section 2 presents a brief segmentation review focusing to graph-based approaches and some aspects related to urban imagery. Section 3 presents the proposed method nemed re-segmentation. We also describe how to build a Region Adjacency Graph and discuss the procedure to find regular shapes on it. Finally, some results and conclusion are shown in Section 4 and Section 5, respectively.

2 SEGMENTATION BASED ON GRAPH

The proposed segmentation method is called re-segmentation because its input is a previously over-segmented image and a merging strategy is applied to generate a new regions set. Methods such as watershed (Duarte et al., 2006; Felzenszwalb and Huttenlocher, 2004; Tremeau and Colantoni, 2000) and region growing (Bins et al., 1996) can be used to produce the input segmentation. Spectral properties of the regions are also input data and each region can be connected to its neighbors when succeeding topological operation "touch" (Egenhofer and Franzosa, 1991) is applied. Such connections are stored in an undirected graph and the distance between the nodes, also called weights, is defined by the difference of their attributes.

Subsequently, a graph processing stage is performed. Connected regions are merged when their attribute values are similar. The graph is built in a structure called Region Adjacency Graph (RAG) (Schettini, 1993). The strategy used to join the nodes is the principal characteristic of our re-segmentation approach, discussed with more detail in Section 3.

2.1 Region Adjacency Graph

A Region Adjacency Graph is a data structure which provides spatial view of an 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 (Tremeau and Colantoni, 2000). Figure 1 depicts a simple RAG of a synthetic image.

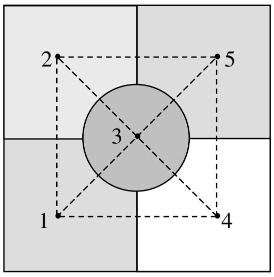


Figure 1: RAG example – Image with 5 regions and their connections.

The RAG can be covered, merged, and partitioned in different manners in accord with the expected results. For example, (Tremeau and Colantoni, 2000) cover the graph and join a regions set (or vertices) if its spectral distance is enough small. In this case, the graph weights correspond to each region mean value. (Duarte et al., 2006) use the so called hierarchical social metaheuristic for the merging operation, which is based on human social behavior. First of all, the regions are joined in a randomly way generating a set of solutions controlled by groups of objective functions. Iteratively, each group tries to improve its objective in a cooperative fashion or competing with the neighbor groups. The ambivalence between social cooperation and competition aims to maximize the quality of the results.

In the other hand, (Lezoray et al., 2003) apply a preprocessing stage to smooth the RAG at each region before merging similar regions. This stage is iterated until the RAG satisfies some stop criterion such as the number of iterations or some similarity threshold. Using a nonlinear function, they perform smoothing operation over the iterations taking into account the regions spectral attributes and connected region neighbors.

Here, we propose a new merging strategy in the RAG structure. The regions are merged if they are similar in respect to their spectral attributes (*e.g.* mean and variance) and if the resultant shape (after merging operation) is regular. In order to carry out this task, firstly, the regions are divided taking into account their classes. In case of urban environment, the classes can be buildings, streets, and trees. Therefore, the regions are classified and several RAG are built through connecting adjacent regions which belong to the same class. Afterward, the algorithm perform the graph searching and merging operations for every classes. The knowledge about the class improves the segmentation accuracy because each class has specific shape regularity measure.

2.2 RAG construction

Let be an image I and a group of M regions, $P_i, i = 1, \dots M$, with $\bigcup P_i = I$. Let be a graph, $G = < V, E >$, where $V = \{1, \dots M\}$ 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 matches one vertex so that $P_i = V_i, i = 1, \dots M$.

Each region is a vertex V_i. Adjacent regions have the weights defined by some spectral distance measure. Table 1 depicts the graph generated from Figure 1. Here, the weights are given by the mean differences between connected nodes. Weights denoted by -1 means that there is not topological connection between the nodes.

Table 1: Graph generated from Figure 1.

	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 RE-SEGMENTATION APPROACH

The proposed re-segmentation approach is based on the RAG construction. The graph is built taking into account the topological relation "touch" between the regions of same class. Therefore, if two regions are connected, *i.e.* touch each other, they are candidate to be graph nodes. In order to perform the re-segmentation the RAGs are preprocessed. This preprocessing stage includes the procedure to find the graph *minimal-cost paths*. However, it is necessary to know the class of each region. If urban objects samples (trees, roads, buildings) are provided the algorithm can treat them conform with their own properties. Another important parameter is the object regularity used to merge the regions. For instance, roads and trees can be assigned to rectangular and irregular shapes, respectively, in the merging operation.

Figure 2 shows the diagram of our re-segmentation approach. Based on input patterns, as those shown in Figure 3, it is possible to define different strategies to merge the regions. Our objective is to merge regions so that new larger regular objects are obtained. For objects with irregular shapes, similar regions are merged based on previous classification and their spectral attributes. The process finishes when there is no more regions to merge.

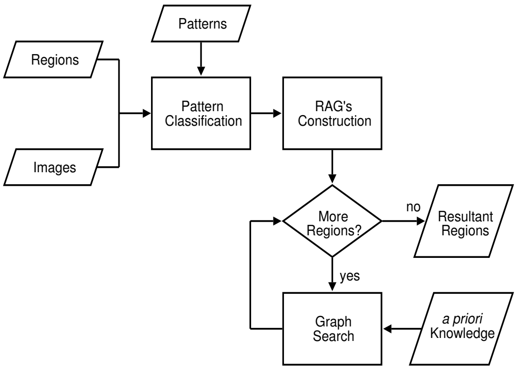


Figure 2: The re-segmentation diagram.

3.1 Pattern classification

The pattern classification procedure is a very important task in our approach. It reduces the attribute space and allows the algorithm to work with few data in the process of finding out regular shapes. In this stage, similar regions are merged for further processing.

Firstly, a supervised classification is performed in order to classify the regions in accord with their pattern. Figure 4 presents a resultant classification using the Self Organizing Maps (Kohonen, 2001) and the three classes depicted in the Figure 3. After the classification, the RAGs are built by connecting adjacent regions belonging to the same class. Finally, the next stage tries to find the best way to connect the graphs, to cut or merge the nodes so that the resultant regions have better shape regularity.

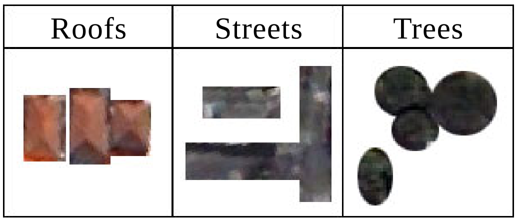
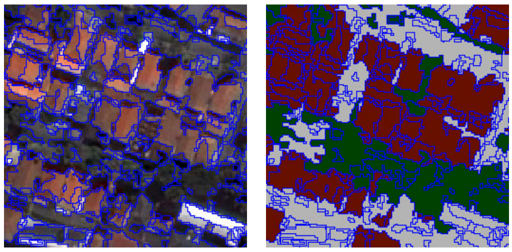


Figure 3: Input Patterns.



(a) (b)

Figure 4: Pattern classification: a) input regions, b) classified regions.

3.2 Minimun-Cost Path

Several scientific problems related to connected elements can be associated to the general problem of finding a path through a graph (Hart et al., 1968). It provides a structure whose nodes are connected to one or more neighboring regions.

Several algorithms to find the *minimum-cost path* in a RAG have been proposed in the literature (Falcão et al., 2004; Shi and Malik, 2000). A minimum-cost path is a set of edges that connects all nodes in a graph without cycles. As this graph connects all regions belonged to the same class, a minimum-cost path represents the best way to find the cuts.

Regarding the urban imagery, the graph edges represent the regularity measures of the regions obtained by the union of two or more sub-regions. The problem is to find out which regions must be merged or not. Next section, we will discuss about the parameter Q that indicates how rectangular a region is, independently of rotation and scale. The objective is to merge regions to generate new objects with shapes more appropriate to urban objects.

The following algorithm summarizes the proposed approach shown in Figure 2:

```
Get input over-segmented images;
Classify the regions (identify the classes);
Build RAGs for adjacent objects of same class;
For each RAG, find the best merging arrangement:
| Find minimal-cost path;
| Calculate regularity measure;
| Perform path cuts;
| Merge connected nodes;
Return resultant regions.
```

3.3 Rectangular objects generation

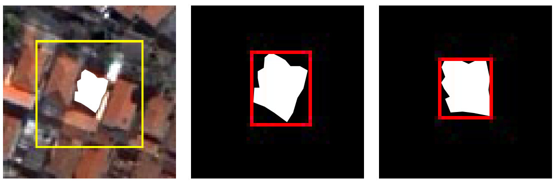
Some good examples of rectangular regions for urban imagery are roofs and streets. However, in some cases the segmented objects do not preserve such rectangular shape; they are broken apart into smaller irregular objects. Therefore, our aim is to join such over-segmented regions.

In order to identify the object rectangularity degree we calculate the ratio between its area $AREA(P_i)$ and its bounding box area $AREA(BOX(P_i))$. Due to the rotation, this measure can not correctly represent the object regularity. Thus, a preprocessing step is performed in order to transform the retangularity measure invariant to rotation.

Given an object P_i and its internal points coordinates $C = \{\{x,y\}|\{x,y\} \in P\}$ the eigenvectors are calculated. Taking the first eigenvector the main angle of P_i, α is obtained. Thus, a new region R_i with bounding box $BOX(R_i)$ is created by rotating it in relation to the angle α. Afterward, the unbiased parameter Q is obtained as following:

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

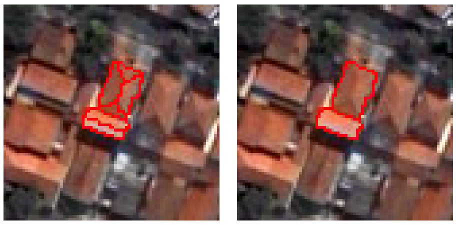
The range of Q is [0, 1]. The more rectangular the object P_i, the closer to 1 is the parameter Q. Figure 5 shows an example of a rectangular object with $Q \approx 1$.



(a) (b) (c)

Figure 5: Rectangular objects identification: a) input region, b) the region and its bounding box, c) the rotated region and its new bounding box and $Q \approx 1$.

At this stage, the algorithm aims to find rectangular objects. If irregular objects are found, two operations are performed: cutting and merging. The objective of these operations is to generate regions whose parameter Q is about 1. As we can observe in Figure 6, some regions belonging to the same class can be split into smaller regions instead of being merged in the initial segmentation process. These are the main problem that our algorithm proposes to solve.



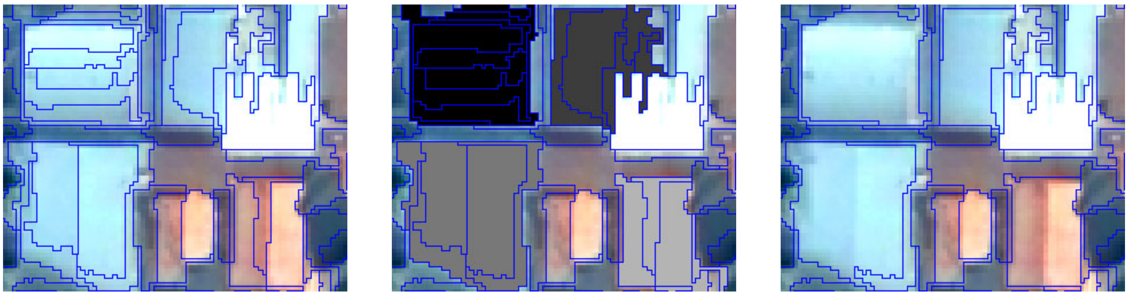
(a) (b)

Figure 6: Objects merging process: a) Connected regions, b) re-segmentation taking into account the rectangular shaped regions.

4 PRELIMINARY RESULTS

This Section presents some experimental results obtained by our re-segmentation approach. The method was tested for Quickbird images of urban regions. For the first experiment, a segmented image superimposed on the original image (300×250 pixels), some connected nodes (represented in different colors) and the resultant re-segmentation are shown in Figures 7a, 7b and 7c, respectively. The over-segmentation was obtained by the region growing method implemented in SPRING (Câmara et al., 1996). In Figure 7c we observe that some regions did not merge although they look like spectrally similar. This is due to the fact that the approach aims to merge only those regions which originate rectangular objects. Other merging or cutting operations that originate irregular objects are not performed. Consequently, the segmentation gets more adequate results. In this case, the algorithm took 37 seconds to generate the re-segmentation.

The second experiment took an image (256×256 pixels) as shown in Figure 8. Figures 8a and 8b display the regions superimposed on the original image and the resultant re-segmentation, respectively. The over-segmentation also was obtained by the region growing method implemented in SPRING. The image presents several instances of roofs that are broken apart in the segmentation process as shown in Figure 7a. It is important to emphasize that the segmentation is the key step for further image analysis. After applying our approach, posterior stages of image recognition or even geographical tasks can be more accurate or adequate to the application. In spite of using small



(a) (b) (c)

Figure 7: Image re-segmentation: a) regions superimposed on the image, b) some regions connected in the RAG, c) final re-segmentation.

image in this experiment, the number of input over-segmented regions is very high. In this case, the algorithm spent 216 seconds to accomplish the complete re-segmentation process.

5 CONCLUSIONS

A new approach for image re-segmentation and some aspects of its implementation have been described. Moreover, in order to show the potential of our approach two experimental results have been presented. The main contribution of this paper is the proposed strategy to find regular regions in the urban imagery. The re-segmentation approach uses spectral and shape attributes as well the thematic map to define the merging and cutting strategies in the RAGs.

The algorithm complexity including the graph searching operation is $O(n^2)$. One way to improve its performance is generating a Minimum Spanning Tree (MST) before the graph searching procedure. Nevertheless, the MST generation has also a high cost. Therefore, research have to be done to find out the attributes set used to find the MST, which is not a trivial task.

The algorithm has been developed in the Free C++ Library called TerraLib (Câmara et al., 2000) available at `http://www.terralib.org/`. Preliminary results presented in this paper still have some errors mainly due to the input segmentation. This process, in certain cases, merges some objects that should be broken apart. Future works include the algorithm optimization for faster execution and implementation of different approaches for the graph cutting operation.

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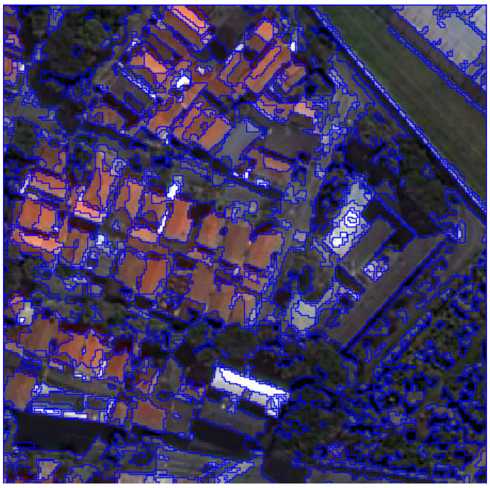

(a)

(b)

Figure 8: Urban image re-segmentation: a) Regions superimposed on the image and b) final re-segmentation.

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