A System to Detect Residential Area in Multispectral Satellite Images

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Abstract

In this paper, we propose a new solution to extract complex structures from High-Resolution (HR) remote-sensing images. We propose to represent shapes and there relations by using region adjacency graphs. They are generated automatically from the segmented images. Thus, the nodes of the graph represent shape like houses, streets or trees, while arcs describe the adjacency relation between them. In order to be invariant to transformations such as rotation and scaling, the extraction of objects of interest is done by combining two techniques: one based on roof color to detect the bounding boxes of houses, and one based on mathematical morphology notions to detect streets.
To recognize residential areas, a model described by a regular language is built. The detection is achieved by looking for a path in the region adjacency graph, which can be recognized as a word belonging to the description language. Our algorithm was tested with success on images from the French satellite SPOT 5 representing the urban area of Strasbourg (France) at different spatial resolution.

Keywords: *Vegetation and water indices, Clustering, graph theory, mathematical morphology, House detection, Road detection, residential area detection, complex structures.*

1. Introduction

The remote sensing community is interested in extracting the largest amount of information from the images of high resolution. Detecting complex structures (composite object) such as park and residential areas is of very high interest, it can provide a solution to the automatic map generation problem.
However street maps that are built manually are incomplete and are expensive in time and money. It is necessary to develop fast and automatic processing of these images. On high-resolution images, conventional algorithms based on the classification of pixels or regions are not efficient enough. Indeed, the high resolution of these images (GEOEye-1: 0.41m) gives the possibility to see complex structures such as residential areas made up of several components (houses, forest, streets) spatially organized. To detect automatically these structures, it is necessary to take into account the notion of spatial relation. In order to take into account this notion, two kinds of method can be found in the literature: The first one is based on co-existing individual objects approach [1]. It is based on the existence of objects or a collection of objects and relations between these objects. The second one uses graphs to represent segmented images [2], RCC8 system is used in order to build a graph based description of the relationships between the regions of an image. This approach gives the possibility to represent in a very convenient way, the spatial relations between different regions or objects in an image. Moreover, the graph theory provides some very interesting algorithms such as graph matching algorithms [3,4,5]. These algorithms were used successfully to compute the similarity degree between two shapes or two patterns [6,7]. We propose in this paper to use the second approach to detect automatically complex patterns in high-resolution images. The spatial characteristics of the data are represented by region adjacency graphs. We also propose a way to represent the organization of the pattern that we look for in the image. This model based on the principle of automaton language generator is provided to the system with the set of images that we want to analyze. Then the system returns the images containing the detection of the desired patterns. This paper is organized as follow: In section 2, we describe in detail the architecture of our system. Trees and forest detection is presented in section 3.In section 4, we present methods used for houses and streets detection. In section 5, we present the used method to enhance the segmentation result. Residential area detection with graph adjacency is presented in section 6. Finally, in Section 7, we draw conclusion from this work and discuss future works.

2. The System Description

The system description is given in Fig. 1. In the following, we detail each step of the processing detection. First, we begin with description of the preprocessing step.

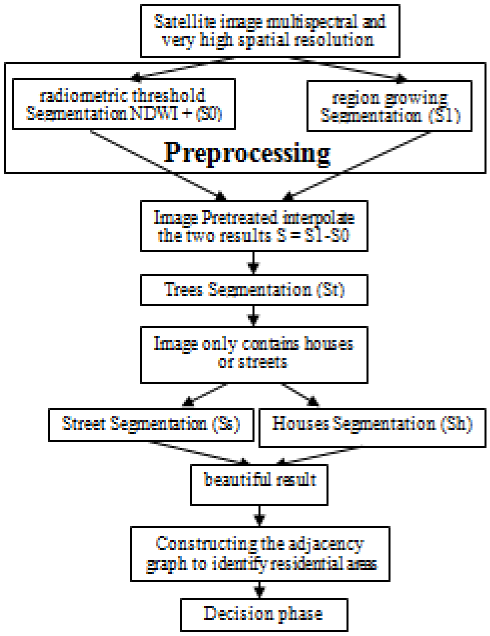


Fig. 1 The system architecture.

2.1 The preprocessing step

The input of this step is a multi-spectral satellite image with high resolution. Two processes are applied. First, illuminating the structures of interest cleans the raw image. Then the image is segmented to make easier the following treatments. These two treatments are done in parallel (each step is independent from each other).

2.1.1 The multispectral segmentation

Most prior work on house and road detection uses either grayscale images or DSM data. Besides grayscale images, we have additional multispectral information, but no surface or site models. We use this information to infer cultural activity and water body. We have used the normalized difference Water index (NDWI) introduced by Gao 1996 [8]:

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \tag{1}$$

Where NIR is the reflectance values in the near infrared and SWIR is Short Wave Infrared (SWIR) channels. The SWIR reflectance reflects changes in both the vegetation water content and the spongy mesophyll structure in vegetation canopies, while the NIR reflectance is affected by leaf internal structure and leaf dry matter content but not by water content. The combination of the NIR with the SWIR removes variations induced by leaf internal structure and leaf dry matter content, improving the accuracy in retrieving the vegetation water content [9].

2.1.2 Region growing segmentation

First, we built an RGB image from the 3 bands 3, 2.1 respectively, and then we apply histogram equalization on the image colors. A region growing based segmentation is applied to extract houses and streets. The trees and forests are extracted by using the linearized vegetation measure. Fig.2 shows the very high-resolution imagery, and the result of application of the preprocessing.

(a) (b) (c)

Fig. 2. (a)Example of image colored with system RGB, this image represents the French Strasbourg region. It is obtained with Spot 5 Tue Mar 07 15:03:52 2006.(b) Detection of water bodies and clouds. (c)Result of the region growing algorithm after cleaning (water body and clouds) the image.

3. Trees and forests detection

In [10] Cem Unsalan and Kim L. Boyer use a derived index to detect human activity. They use the linearized vegetation measure from NDVI. But in our case we just have to use NDVI to obtain correct result.
Vegetation indices have been extensively used to estimate the vegetation density from satellite and airborne images for many years. Rouse et al. [11] introduced the normalized difference vegetation index ($-1 \le NDVI \le +1$):

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

Where NIR and RED are the reflectance values in the near infrared and red bands.

Fig. 3 (a) Trees and forest segmentations from NDVI index. (b)Detection of houses and street.

4. Houses and streets detection

In the literature, there are often three main methods to detect houses:
The first one is based on the color of roofs [12,13] the second on the detection of shadows [12,14] or a combination of both [12], and the third is based on shape detection [10]. In our case we want a system that is invariant to changes in the special resolution and scales, that why we combined the two methods [12,10], one based on color and shape to benefit from both advantages.
First we applied a classification based on the red roofs color, and a detection of the bounding boxes of the roofs is achieved.

(a) *(b)*

Fig. 4 (a)Test image. (b) Bouding boxes of the roofs.

Mathematical morphology is a well-known tool to extract regions based on their shapes [15,16]. Then morphologic operators are used to detect streets. We use two basic morphology set operations: dilatation and erosion. Let points be P = (P_1, P_2) , a = (a_1,a_2), b = (b_1,b_2). Let A be a set of points, not necessarily connected in the plane.
The *dilatation* of set A by set B is:

$$A \oplus B = \cup_{b \in B} (A)_b \qquad (3)$$

The *erosion* of set A by set B is:

$$A \ominus B = \cup_{b \in B} (A)_{-b} \qquad (4)$$

Where B is the structuring element.

Then the aim is to identify the elongated subsets which represent possible street segments. For this purpose, we extract lines by applying erosion and dilatation operations, respectively. We define four linear structuring elements: horizontal, vertical and the two diagonals like in [10].

Fig.5 Road Detection after four dilatation and four erosions.

5. Enhancing of the final segmentation result

In order to make easier the detection of residential areas, it is necessary to enhance the final segmentation.
First, all the structures have to be gathered on the same image. Next, the small regions that cannot be structures such as houses or streets have to be removed. It is done thanks to a region growing algorithm which compute the surface, in number of pixels, of each region.

A small area in our AC is defined by:

$$Rs < \sum R / Nbr \qquad (5)$$

With: Rs is the smaller region, R is the regions and Nbr is the number of all regions. A specific color is assigned to each kind of structure: red for houses, blues for streets and green for trees.

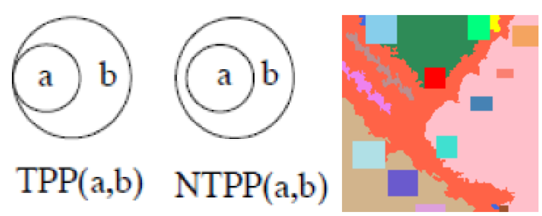
6. Residential area detection with graph adjacency

The last step consists in detecting and counting the number of residential area in the segmented image. Two methods can be applied:

1- Detection of object of interest in an object compound (in our case the object of interest is the houses, and the detection of a house in a structure implies that it is associate to a residential area).

2- Detection of spatial relationships that characterizes the structure by using the graph formalism.

We have applied the second method because the first is very simple, it transferred the problem of location from a complex structure to a problem of patterns detection. Also it does not take into account the spatial relationship between the patterns, unlike the second method. The special relation who characterize the existing of residential area is modeled with the existence of an adjacent houses and trees which are ***surrounded*** by streets. The "surrounded by" notion is modelised by the spatial relationships TPP and NTPP fromm RCC8 system (See *Fig.6a*).



(a) *(b)*

Fig.6. (a) the TPP and the NTPP relationship from RCC8 system to explain surrounded by relation. a ∈ {trees, houses} and b is a street. (b) the different segmented regions.

In this approach it is necessary to define a model representing the spatial organization of the composite object (in our case, residential areas) that we look for in the image. The aim is to retrieve composite objects corresponding to the model in the region adjacency graph representing the segmentation. In the region adjacency graph, each node represents a region and each arc represents a relation of adjacency. It is difficult to represent this model by a graph as we do not know the exact number of houses or trees that should be in the model.
To solve this problem we use the principle of automaton language generator. The principle is explained in *Fig.7*. The set of possible patterns describing a residential area is a set of words belonging to a regular language. The recognition of a word is achieved with a deterministic automaton.

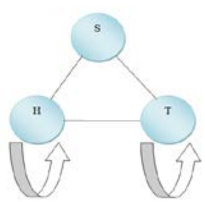


Fig.7 scheme of a generator of residential aria. S is a street, H is a set of houses and T is a set of trees

For example, we can have word like that: SHHHHTTTSTTHHSHTHTTHHS...etc. Then we have to look for the residential area between two S like (HHHHTTT) in the example.
The regular expression is given by: $(S(H^{+}T^{*})^{+}S)^{+}$
In the decision phase, we look for a path in the adjacency graph (each node corresponding to a letter S, H or T) that could be a word belonging to the given description language (in our case, description of residential areas).

Fig.8 the result of detection of residential.

In the test image, three residential areas are found (there is four). This problem is due to the segmentation step and not to the detection step. To solve this problem, the notion of orientation of patterns will be introduced in a future work.

7. Conclusion

In this work, we deal with the detection of patterns representing residential areas. We propose a general methodology which uses graph to represent images. The model representing a given pattern is a regular langage describing all the different possible spatial organization that we can find for this pattern. Our method was tested on different images with different resolutions and rotation and very good results were obtained. In a future work, we need to introduce the concept of orientation in houses detection and we have to test our system on a larger number of images with different rotation and scales. We also have to test our system with other complex structures such as park, airport in order to generalize our solution for a big number of complex structures extractions.

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