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The Study of The Bay of Mount Saint-Michel by Using Graph Theory in The Analysis of Satellite Images

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Abstract

In this paper, a new approach for mapping based on the concept of objects and relationships between these objects is proposed to take advantage from both supervised and unsupervased classification methods. On the one hand, objects obtained after a supervised classification are represented by an adjacency graph model. On the other hand, objects obtained after unsupervised classification are represented by an adjacency graph data, and the goal is to measure the matching between this two graphs in order to improve the results of unsupervised classification in association with those obtained from supervised classification. This study concerned the coastal Bay of Mont Saint-Michel, the data used are from SPOT 5 optical satellite images.

Keywords: *Clustering, graph theory, Classification, graph matching, spatial relations, mapping.*

1. Introduction

Remote sensing techniques allow the extraction and the analysis of large and different type of information provided from height resolution satellite images. Analyzing with relevant the content of this height resolution satellite imagery following a complex process and needs advanced techniques of data mining to provide a solution to the automatic map generation problem [1]. Several algorithms and methods are developed in this purpose to detect complex object from satellite images [1].

The bay of mount Saint-Michel is a coastal area subject to large environmental and anthropogenic pressures. In fact, the natural and human activities increases the pressures facing the coast, need quick solutions for the management of the territory. In this concern, the analysis of remot sensing images play an important role, and specially the study of the coastal environment from satellite imagery can address a variety of fields ranging from simple mapping of the land to the study of the foreshore and hydro-sedimentary dynamics.

Bay of Mont Saint-Michel was chosen as a study site to share its scientific interest which is worn for several decades. This area has also a global reach with environmental and heritage very important. On the other hand, the bay is one of the most complex and most dynamic coast area in the world. The multiple challenges posed by the management of the bay requires a thorough knowledge of this area and its current and future developments.

The bay is a very dynamic environment that is changing rapidly. Satellite images are very well suited for monitoring regularly updated and they allow a multiscale study, in addition to traditional data used by managers. More accurate images is finer, closer now than aerial photographs. Finally satellite images permettes many additional treatments because of their spectral range with infrared. The advantage of using satellite images to study the nearshore been the subject of several works [2, 3, 4].

One of the classical techniques using THR images or called traditional techniques of image processing are based on the pixels or regions are no longer applicable, the community is currently interested in the technical processing of objects and relations between these objects. The interest in such approach is argumented by the possibility to extract the maximum information and have intelligent processing of information in the same way as in the human résonnement.

This paper is organized as follows: section 2 presents the description of the classification system. Section 3 presents the supervised classification. In Section 4, we present the method used in unsupervised classification. In Section 5, we present the construction of adjacency graphs and matching algorithm. Finally, in Section 6, we give the conclusion and some perspectives.

2. The System Description

System description is given in Fig. 1. Two different classification methods can be run in parallel in tow differents processus for the same image mapping, a supervised and unsupervised algorithms are used for this purpose. We will detail each of these classification method following the various stages that make up the system architecture. The supervised classification is performed from samples selection and from ROI (Region of Interest) of each sampled image consiste the critical step in the process of supervised classification. The quality and the suitability of the results will depend on this sampling phase. That is why it is important to select the samples that cover all classes of objects. It is not very clear for a non-expert in the field to distinguish between different objects especially on coastal environment or objects are very similar and in overlapping. So to get a good set of sampling data, we requires the help of an expert (knowledge of the geography of the field), while the second method of unsupervised classification does not require domain knowledge for the processing.

This two classification methods are independent in the system architecture and will be run in parallel (needs multi-threding system). From the classification results of each of these two methods, we will build an adjacency graph. In the case of supervised classification, the system creates a model graph where each node represents a label that corresponds to an object classified by this method and each edge represents the adjacency relation (adjacency graph). For unsupervised classification, the system creates a graph or data each node represents a form found and each arc represents the adjacency relation between these objetcs. Was used in this study the adjacency graph to represent the relationship between the diffents objects (Next-To) that can implicitly express other relationships such as the relationship (surrounded-by) can be expressed by (all the 4 or 8 Next-To an object are the same object).

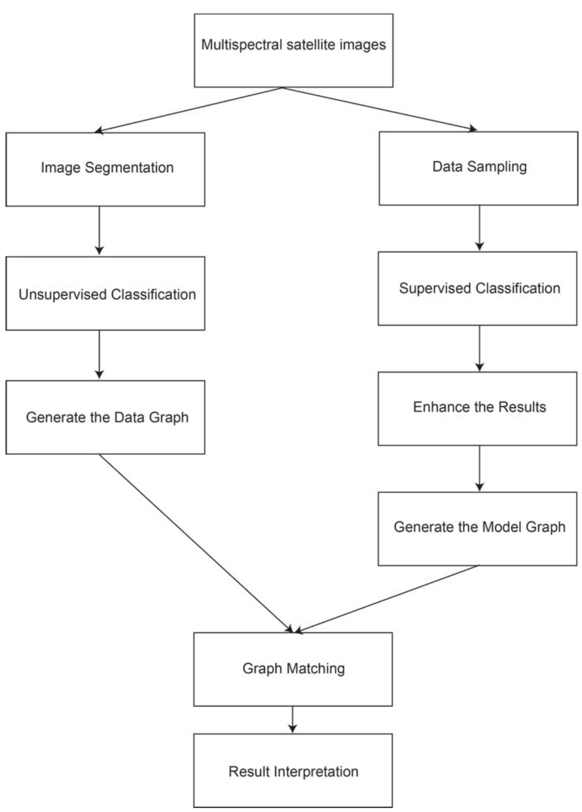

Fig. 1: The system architecture.

3. Supervised classification:

This classification method needs a set of ROI or samples representing the diffirent classes of objects presented in at least one of the sampling images. We applied the standard algorithm of maximum likelihood classification, the major advantage of this method of classification is there short runtime, howevere it can gives an incorrect results, especially in our study area (coastline) where the major objects have a very similar signature spectral and situated in overlapping. For these reasons, if we use only the spectral information in the classification process, we can not distinguished between objects "sea", "water body" and "channel and shallow sea." (Fig. 2)

After finishing the supervised classification, we can apply an algorithm for the correction of the classification based on a set of rules taking into account the nature of the possible neighbors of each classe object found. We apply different rules taking into account the number of neighbors (4 or 8 neighbors) of all pixel situated in the border of two different classes. We present an example and the syntaxe of one rule used in this processing:

- if (label (i, j) == "Wed") and (label (i-1, j) == agricultural areas with low vegetation, bare soil ") or (label (i + 1, j) == "agricultural areas with low vegetation, bare soil") or (label (i, j-1) == "agricultural areas with low vegetation, bare soil") or (label (i, j + 1) == "agricultural areas with low vegetation, bare soil") then label (i, j) == "water channel".

The classe "water" is easily identifiable with this system, and the problem is how to isolate the other classes involved in this main classe (water) . It is possible to isolate this class of objects by performing a numerical thresholding values applied in a single spectral band (monospectral thresholding). Water surfaces are observable by a sensor sensitive to near infrared: all pixels whose numerical value is below a threshold value can be assigned to the class "water" because water absorbs radiation. But it is difficult to distinguish clearly between these subclass (Sea, Channel and shallow sea, river, body of water). To solve this problem, we apply rules based on the notion of object to enhancing the final results. Below, we gives an example of this used rules.

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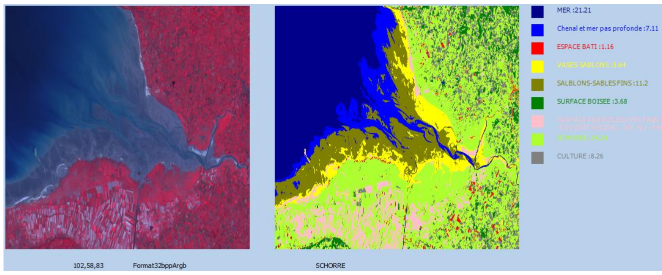

Fig. 2: Results of supervised classification for nine classes.
Is generally the format rules for classification step to improve results take into account the aspect of spatial objects. In other words, it refines the first results of the first classification by introducing the constraint direct vicinity.

- ***If (object classified channel) and (not (Next-To (object, sea))) then becomes streams, and bodies of water.***

Noticed that these rules can solve the problem of water classes, but these do not help to know other informations : the extracting of the salt marsh, the direct neighborhood information of the object. We use neo-canal information to separate between two objects and to limit the salt marsh on the map of the neo-gradient. We use the NDVI (Normalized Difference Vegetation Index) neo-Canal introduced by Rouse et al. [5].

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad (1)$$

It varies between -1 and 1. This index is very efficient for the detection of active vegetation, We use also another index to highlight the mineral surfaces, bare soil, called the index of Brilliance (IB) given by the following formula:

$$IB = \sqrt{(PIR^2 + R^2)} \qquad (2)$$

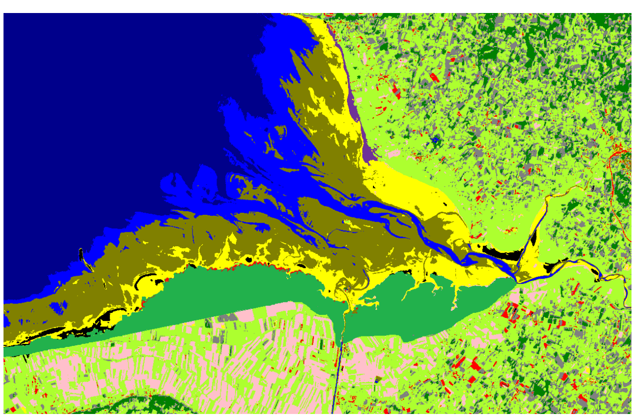

Fig. 3: The final result of supervised classification.

4. Unsupervised classification:

This type of classification is guided by the segmentation phase. The growth areas segmentation algorithm was used with a small changes in the settings to better adapt the algorithm to this area study (coastline area). The idea is to group pixels with the same gray level into the same group (cluster), the major problem faced here is that a small change in grayscale value of a pixel will assign the pixel to a new group. For this, we used a parameter k = 5, adapted to group the pixels which have the same gray level (+ / - k) and respecting to initial grayscale of the starting pixel. We recompute the mean grayscale of the for each iteration using the formula (4- neighbors):

NewNg = (OldNg * 2 + ¼ (Ngg + Ngd + Ngh + Ngb))/ 3
(3)

With: NewNg: the new gray level of the pixel.
OldNg: the old gray level of the pixel.
NGG: the gray level of the left neighbor.
Ngd: the gray level of the right-hand neighbor.
Ngh: the gray level of the neighbor above.
Ngb: the gray level of the neighbor below.

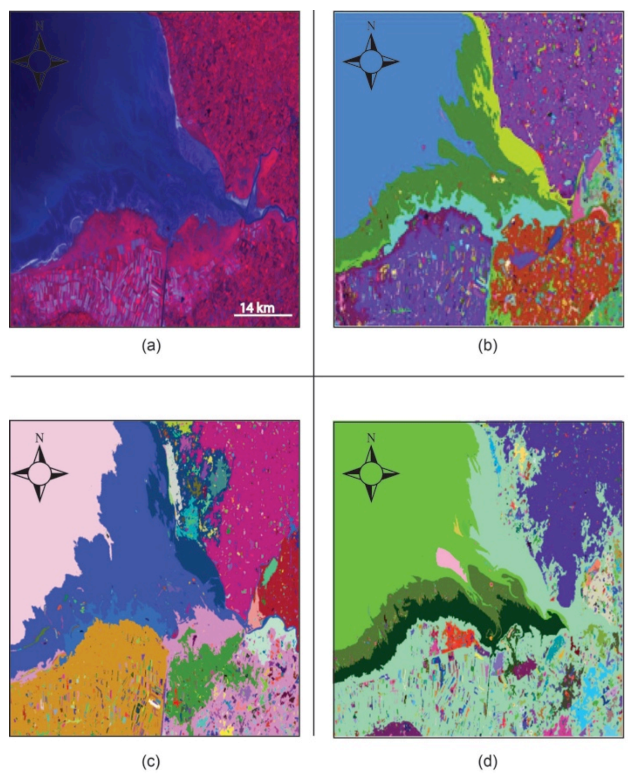

Table 1: (a) original image, (b) segmenting results with k = 5, (c) segmentation results with k = 10, (d) segmentation results of NDVI neo-canal and using k = 5;

In a second step, we applied the segmentation algorithm on a the gradient map to determine the border of the different object, then we calculate for each region the index of consistency between each region and its neighbors. According to this index, we will grouped the similar region into a single region. The consistency index between two regions is given by:

$$IC = \frac{1}{i*j} * \sum_i \sum_j (|PiR1 - PjR2|) \quad (4)$$

With IC: the consistency index.
PIR1: pixel i of region 1.
PjR2: pixel j of region 2.

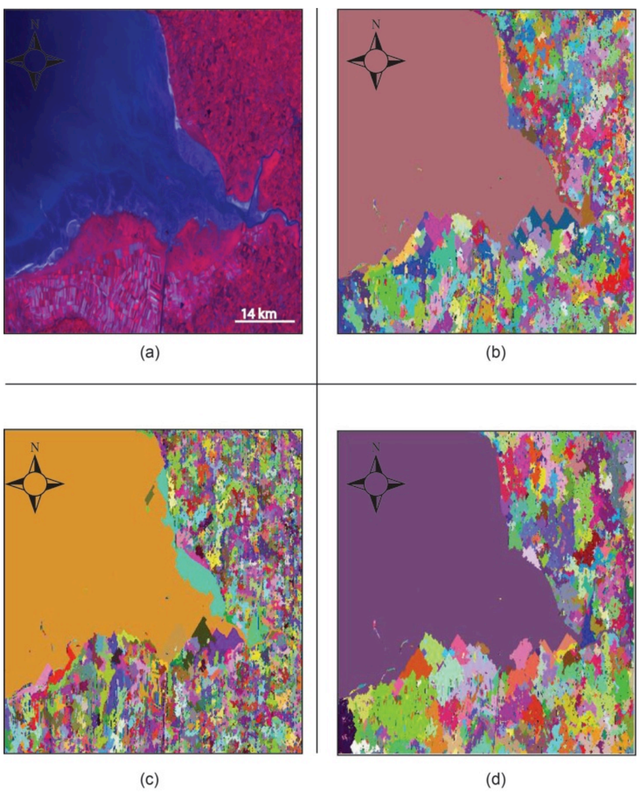

Table 2: (a) original image, (b) segmenting with k = 5, CI = 15, (c) segmentation with k = 10, IC 20 =, (d) segmentation of NDVI from k = 5, IC = 20;

5. The construction of the two graphs and their matching

This part contains three subparts, in the first subpart, we construct a model graph from the supervised classification: nodes represent labels and the average gray level and the size of each class (number of pixels) in each object and the arcs represent the adjacency relationship (direct neighbors).

In the secound subpart, we built a data graph from unsupervised segmentation respects (k = 10, CI = 25). Nodes represent the average gray levels for each region and size of each class. In general, the size of data graph is greater than that size of the model graph.

In the second part, we group the nodes of each graph separately using the given gray level value close to the gray level of the node in the graph model and the regions include the turn of nodes in the graph model and each cluster is recalculated at average gray regions by the formula (3). Spatial information used here is the relationship of Next-To as bijective relation.

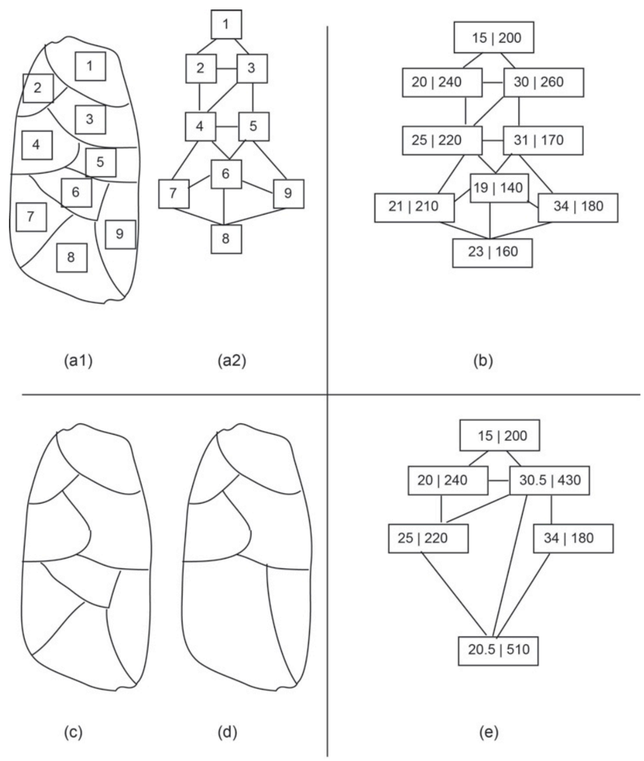

Fig. 4: (a1) the result of the unsupervised segmentation, (a2) its adjacency graph, (b) the composition of the value nodes left the gray level and the right size of the region, (c) the result of the first iteration, (d) the final result with Nb-node = 6, (e) the final result graph.

However, an ambiguity in the decision phase can appeared when the system faces the situation where there is more than one neighbor node checked the condition (same gray level and both are neighbor of the initial node). In this case, the decision will be for the largest region (number of pixels). In other words, this node will be added to the critical node that represents the largest region. At the end of this stage, the system left two graphs having the same number of nodes and labeling graph data is as following:

For each node in the model graph model do:

Find the node in the data graph that minimizes *distance*, this distance is calculated by the formula:

$$\text{distence} = \sqrt{(\text{NGM} - \text{NGD}) * (\text{sizeM} - \text{sizeD})} \quad (5)$$

if size (data node) is less than size (model node) then:

data node ← model node.

Delete all the pixels belonging to this node in the model graph.

- Give to this node of data graph the same label as the corresponding node of model graph.

repeat until have covered all model graph

Return the data graph.

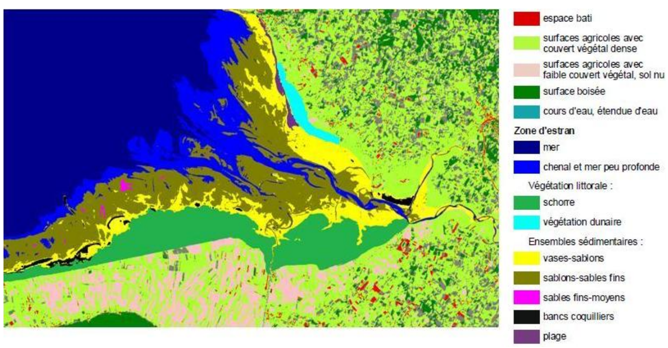

Fig. 5: The final map after the application of the graph matching algorithm and the labeling.

The table below gives a description of the entire geographic objects found and their neighbor, after applying the graph matching algorithm for the SPOT 5 satellite image of the bay of Mount Saint-Michel.

Object	***Neighbors***
Sea	Channel and shallow sea
Channel and shallow sea	Sea fine-sand sand fine sand middleweight Vases shellfish beds rivage
Fine sand	Channel sands and deep sea middleweight sand Vases shellfish beds
Means sand	Channel and deep sea fine sand Vases shellfish beds
Vases and fine sand	Channel and deep sea fine sand dune beach means shellfish beds Shore Woody Bare soil surface Agricultural dense built
Shellfish beds	Channel and deep sea fine sand middleweight Vases and fine sand Shore
Beach	Shellfish beds sand middleweight Vases and fine sand Shore Build
Dune	Vases range fine sand shore Bare soil Agricultural dense built
Shore	Channel and deep sea vases fine sand dune shellfish beds built Sol naked Agricultural dense
Watercourse	Bare soil surface beach Agricultural dense
Surface Woody	Vases fine sand rivers bare soil Agricultural dense built
Bare soil	Vases fine sand dune shore rivers Woody Agricultural dense built area
Dense agricultural	Vases fine sand dune shore rivers Woody Bare soil surface mount
Built	Vases range fine sand shore dune woody sol dense agricultural

Table 3: Table of knowledge of the entire geographic components with their neighborhoods of the bay of Mount Saint-Michel. according to the results obtained in Fig. 5.

6. Conclusion

In this work, we deal with the detection and the representation of differents geographic patterns of the bay of Mount Saint-Michel. Two different segmentation methods are used: the first one based on a supervised algorithm using set of geographic patterns for the learning phase and the secound is unsupervised algorithm. Both of this algorithms can be used separately or in parallel for mapping the coastal area. All the patterns are represented in the form of adjacency graph for helping the clustering with the introduciotn of spatial information in the classification process. Mapping and the labelling of all geographic patterns are performed from the model graph built from the results of supervised classification and the data graph obtained from the unsupervised classification. Our algorithm was tested with set of optical SPOT 5 images with different resolutions. This study provide more than 14 differents geographic objetc with their neighbor and can be used for the monitor of the bay of Mount Saint-Michel from multitemporal images.

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