A recursive unsupervised neural network approach to extract concepts from remote sensing images

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ABSTRACT

This paper describes a novel recursive and unsupervised learning method for extracting information from remote sensing images. Usually, the amount of data on these images is large, and the number of mixed pixels is important. Therefore, an unsupervised learning or clustering can be useful in the analysis of these data. An unsupervised neural network algorithm is used for initial segmentation of the spectral data space of remote sensing images. To discover concepts, a recursive region aggregation method is proposed. This method has been tested and validated with several remote sensing images. An urban zone image is used to illustrate this learning method which provides a way for fast and automatic segmentation of remote sensing images. In order to improve the efficiency of concept extraction some spatial information is incorporated into the aggregation procedure.

Keywords: Machine learning, neural networks, Self Organizing Maps, remote sensing, image segmentation, classification

1. INTRODUCTION

Unsupervised machine learning methods are commonly used in domains where the amount of data is large and background knowledge is weak. These methods derive useful generalization from the data. This kind of learning is sometimes called “learning without a teacher”. Unsupervised learning methods provide a “clustering” or a “segmentation” of a data space. The domain of remote sensing image classification is appropriate for the application of these methods. The amount of data is important, and tools for helping their analysis are often necessary. In general, segmentation tools provide a pixel-by-pixel classification of the images.

For certain applications, where the resolution of objects is small and the number of mixed pixels high, the pixel-by-pixel classification presents several limitations. For instance, at a 20×20 meters resolution, remote sensing images of urban zones have a large amount of mixed pixels representing a composition of various objects. The pixel-by-pixel classification of the spectral space produces many irrelevant classes of mixed-pixels.

The spectral data are easy to use and to clusterize, but remote sensing images provide more information than spectral data. It will be shown, that the pixels linked in the grid of an image encode spatial relations, that are important to discover thematic objects within the image. It should be mentioned that the computing of spatial relations is very costly and in some cases the computing time may be prohibitive.[1]

Many image analysis algorithms use only the spectral information of remote sensing images. Other methods, such as instance region-growing,[2,3] use the spatial arrangement of the pixels to do image segmentation. They are based mostly on the use of local variations of the spectral values. Therefore, their usage in remote sensing images analysis is limited, since they do not consider spatial information, nor they produce spectral classes. Few classification methods[4] use both spectral information and spatial relationships.

The originality of our approach is based on a recursive construction of remote sensing objects using both spectral and spatial information. This method uses Self Organizing Maps (SOM)[5,6] described in Section 2. Section 3 discusses the application of this method to a segmentation of the spectral space of remote sensing images. Section 4 presents a recursive method which adds regions and uses SOM on spectral and spatial information. Section 5 presents some concluding remarks together with some perspectives of this work.

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2. UNSUPERVISED LEARNING

Unsupervised learning is a process of deriving useful generalizations from data sets. This process is sometimes called "learning without a teacher" and can viewed as a "clustering" of the data. One of the best known unsupervised neural network methods is the Self Organizing Map. This method is robust, and provides quick segmentations of a data space. Although SOM are used in the approach presented in this paper, any other unsupervised method such as K-means, conceptual clustering, could be applied.

SOM are made of a network of neurons interconnected with their neighbours. Each neuron or cell is defined by its reference vector which has the same dimensionality as the data space of the application. The number of neurons and the topology of their neighbourhood are defined by the user. The reference vector can be viewed as the center of a class in the data space. At the beginning of the learning process, the weights of reference vectors are initialized randomly and then they evolve in order to better fit the data distribution while the map is learning. The map is trained until it fulfills a satisfaction criterion. A satisfaction criterion can be as simple as to stop learning after an arbitrary number of epochs, where an epoch corresponds to a presentation of all the training examples. This criterion can be more complex. It can, for instance, be related to statistical properties of the map. At the end of the learning process, each neuron of the map defines the center of a class.

The learning algorithm of a Self Organizing Map is presented below:

Algorithm 1 Learning algorithm of SOM

```
while Stopping criterion is not satisfied do
  Randomly choose an example
  Find the closest neuron from this example in the map
  Modify the reference vector of the neuron in order to bring it nearer to the example
  Modify also, but slightly, the reference vector of the neighbouring neurons.
end while
```

An in-depth description of SOM is out of the scope of this paper. A more detailed presentation can be found in the works of T. Kohonen.[5,6]

It is important to notice that the training of SOM provides one segmentation among others which satisfies a given stopping criteria. There is no guarantee to find a unique best segmentation for a problem. Usually, two different learning processes produce different maps due not only to randomized initializations of the weights, but also to the presentation order of examples. Figure 1 illustrates an example of a segmentation of a 3-dimensional spectral data space using a Self Organizing Map. The coordinates x, y and z of the figure correspond to the spectral values of the bands XS1, XS2 and XS3 of a SPOT image. Each point of the data space has a grey level defined by the nearest node in the map. The patchwork in grey level of this image illustrates the distribution and segmentation of the data. It is obvious that with such a continuous data distribution one may obtain many different segmentations.

3. UNSUPERVISED SPECTRAL IMAGE SEGMENTATION

3.1. Segmentation of the spectral data

Classification of remote sensing images can be considered as a spectral data clustering problem. An unsupervised learning method is used for doing the segmentation of the spectral data space. In the case of SPOT images, each pixel of the image is described by three 8-bits spectral values (between 0 and 255). A Self Organizing Map can be used to produce the segmentation of these data and thus, to classify pixels according to their spectral values. The size of the map is defined arbitrarly, and in general, it corresponds to the user requested number of classes. For instance, a 4×4 neurons map allows up to 16 classes to be discriminated after the learning process.

3.2. Experiments

Our experiments were carried out on different SPOT images covering the cities of Strasbourg and Mulhouse, in France, and the Himalayas, in Nepal. The images of Strasbourg and Mulhouse represent urban areas with small objects, while the Nepal one covers mountainous zones and weakly inhabited areas with large homogeneous objects such as pastures, forests, soil. In this paper, to illustrate our approach, an extract of the SPOT images representing the North-East part of Strasbourg will be used. The image size is 200×250 pixels, where each pixel is described by three spectral values. The number of classes in the

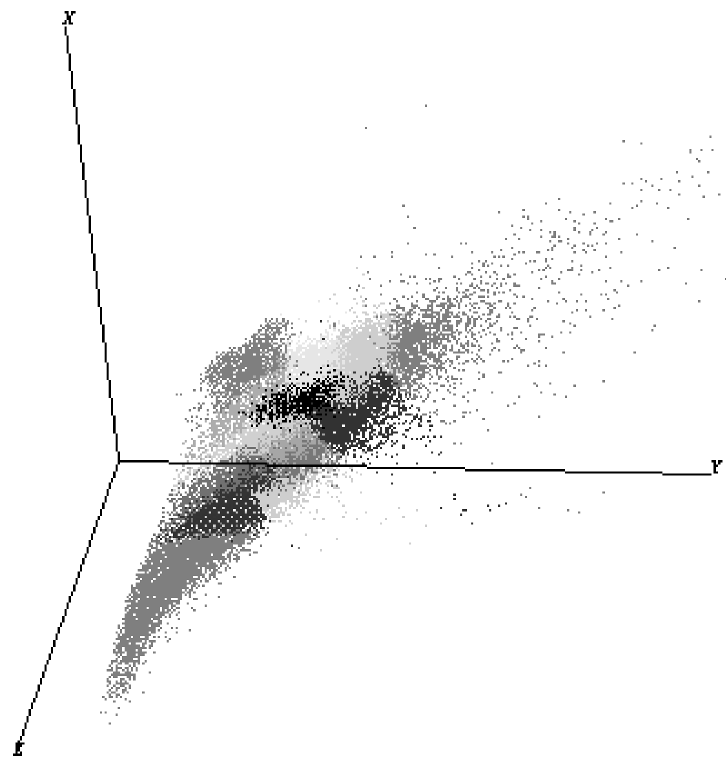


Figure 1. Three-dimensional plot of a segmentation of spectral data space on a SPOT image

experiments has been given by the field experts, remote sensing cartographers. Three classifications have been performed with 9, 16 and 25 classes, therefore, maps with 3×3, 4×4, and 5×5 neurons were applied.

Figure 2 represents the spectral classification of the pixels of a SPOT image given by a 3×3 neurons Self Organizing Map. Some spectral classes can be easily labelled. For instance, the one representing rivers, the one corresponding to areas covered by forest or vegetation, and that of large buildings. Other classes, regrouping non homogeneous zones, are more difficult to interpret since they correspond to a mixture of objects.

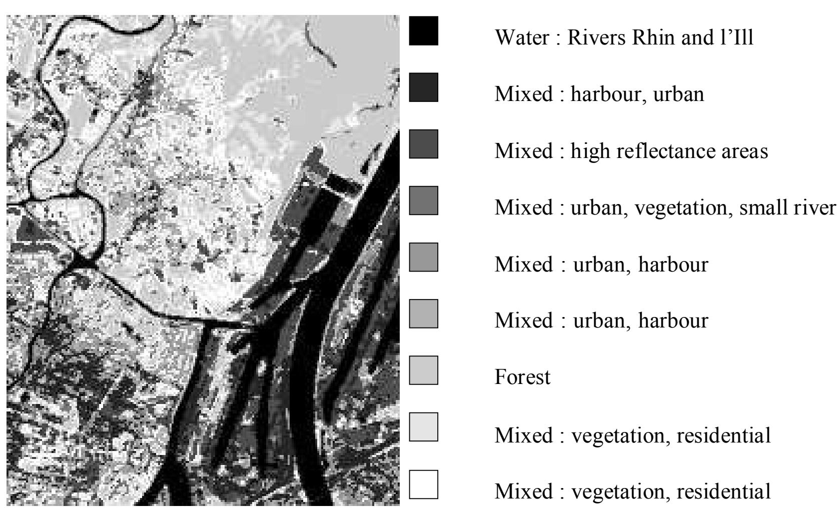


Figure 2. Spectral classification with a 3×3 neurons map

3.3. Discussion

As illustrated, the clusterization of the spectral space with an unsupervised learning method generates a set of classes which segments the data space. If the derived classes are not satisfactory, the next segmentation can be performed by modifying parameters such as the number of classes, the stopping criterion, or the initialization values.

The computing time to train an Self Organizing Map depends on: the amount of data, the selected stopping criteria, and the size of a map. If the selected stopping criterion is simple, e.g. to stop after a small number of presentations of the whole data set, the computing time is very short. For instance, it only takes a few seconds for 40 epochs of learning with a small 250×200 pixels image on a Pentium II Workstation with a 4×4 map. Therefore, the user may try interactively different parameters in order to get an acceptable spectral segmentation.

This method uses only the spectral information of the data and not the spatial properties. It is adequate for images where the objects are large and homogeneous in terms of spectral values. Nevertheless, this method is not appropriate when the size of many thematic objects is similar and equal to one pixel or when there are different objects covered by one pixel. The semantics of one single mixed pixel is not easy to discover. However, a group of mixed pixels sharing spatial relations may have a meaningful interpretation. It should be noticed that, it is useful and more interesting, from the user point of view, to label spatial regions rather than only spectral classes of pixels.

4. RECURSIVE UNSUPERVISED IMAGE SEGMENTATION

4.1. Introduction

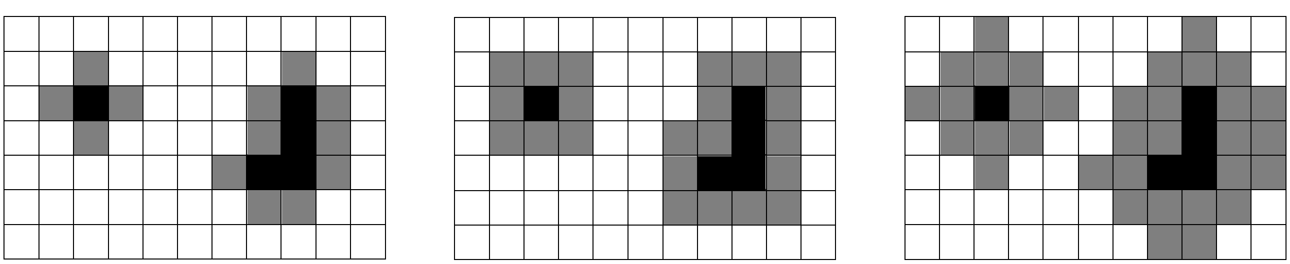
The concept extraction algorithm, based on the available spectral classification of remote sensing images, generates initially regions, which are then aggregated and re-classified recursively.

The regions are created by a process that considers not only spectral but also spatial characteristics of the regions or objects. Indeed, in order to classify and extract objects from remote sensing images, it is interesting to take into consideration also spatial relationships. Many spatial properties can be used, but some of them can considerably increase computing time. Therefore, to reduce the computing complexity, our algorithm uses only simple properties such as the distribution of classes in the neighbourhood of a region. This design decision allows us to keep an acceptable computing time for an interactive use.

4.2. Aggregation

The first part of our approach consists on adding regions which share some properties. Two kinds of properties are considered: the class identity and the proximity according to a radius of region neighbourhood. The radius of region neighbourhood allows the user to define the distance used for aggregating regions. The greater this radius is the more distant regions can be added, but also the greater the computing time needed to explore the neighbourhood. The distance considered between two regions is the usual Euclidean distance between the two closest pixels of the regions: distance $= \sqrt{(x_1 - x_2) + (y_1 - y_2)}$ where (x_1, y_1) and (x_2, y_2) correspond to the coordinates of these two pixels. Other definitions of distance could also be applied.[7,8]

Figure 3 illustrates the effect of using different radius values for the neighbourhood of two objects. In this figure, the pixels in grey color correspond to the neighbourhood of the ones in black. Notice that, when the radius is equal to 1 the neighbourhood corresponds to the 4-connexity, but when it is between 1 and 2 excluded, the neighbourhood corresponds to the 8-connexity. The last example with a radius of 2 illustrates a more extended notion of connexity used in the algorithm.



radius = 1.0   1 < radius < 2   radius = 2.0

Figure 3. Illustration of effect of different radius of neighbourhood

The following algorithm describes the aggregation process of regions.

Algorithm 2 Aggregation algorithm

```
for each class do
  for each region R of this class do
    Compare the distance between R and the each other region of the same class
    if the distance between two regions is lower or equal to the radius of neighbourhood then
      Aggregate the two regions
    end if
  end for
end for
```

Initially, at the first step of the method, each pixel is considered as a region and its class corresponds to the spectral class of the pixel. The process of aggregation starts with these "one pixel wide" regions. Figure 4 illustrates the aggregation of pixels into regions with radius of 1, 1.5 and 2 respectively for the three examples. In this figure, the grey level of each pixel corresponds to its class and the number to the region in which it has been aggregated.

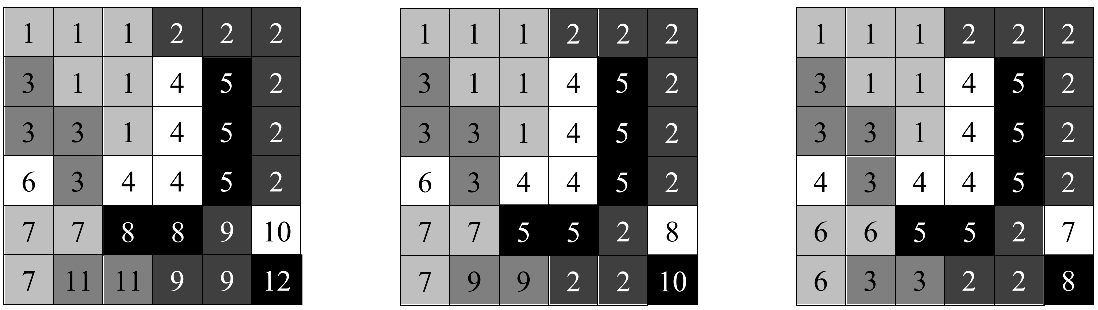


Figure 4. Aggregation of pixels into regions

4.3. Classification of regions

The second step of our approach consists of region classification according to spatial and spectral features. The chosen spatial features are related to the distribution of classes in the neighbourhood of each region. The radius of the neighbourhood is defined by the user. As mentioned before, the larger the radius, the more distant spatial properties can be considered, but also the bigger the computing time is needed to calculate the spatial relationships.

The chosen spectral features correspond to the standard deviation and the average value of a region for each spectral band. A feature vector, composed of two parts, is built for each region. The first part of the vector contains information about the spatial distribution. The second part of vector contains the spectral statistics. Figure 5 illustrates both the effect on spatial distribution of the choice of different neighbourhood radius, and the corresponding vector for the white region (marked by "r"). The grid in the left uses a neighbourhood radius of 1, the one in middle a radius of 1.5 and the one in the right a radius of 2.

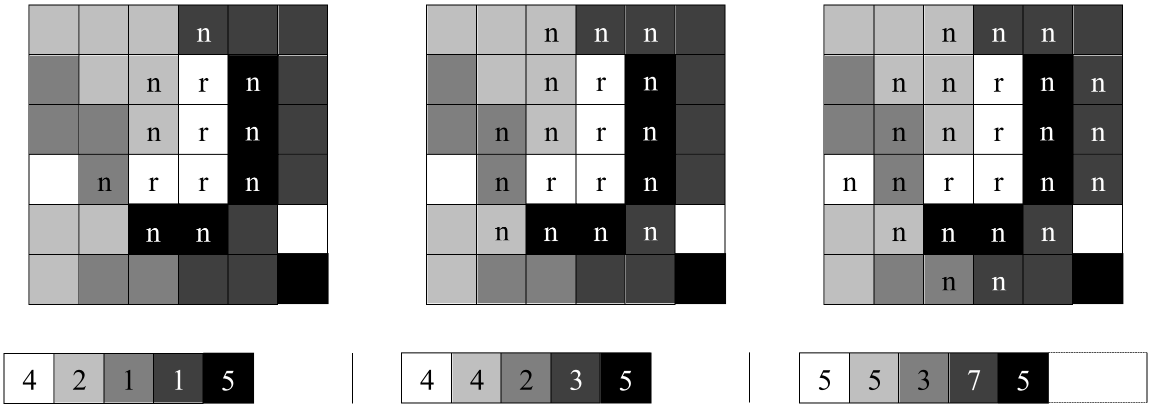


Figure 5. Spatial distribution of classes with different neighbourhood radius

Figure 6 shows the new set of vectors generated by the algorithm for all the regions of the same example. The regions are created with an aggregation radius of 1.5 and a neighbourhood radius of 1.5. In both figures, the right part, corresponding to the spectral statistics of the region, is left unfilled.

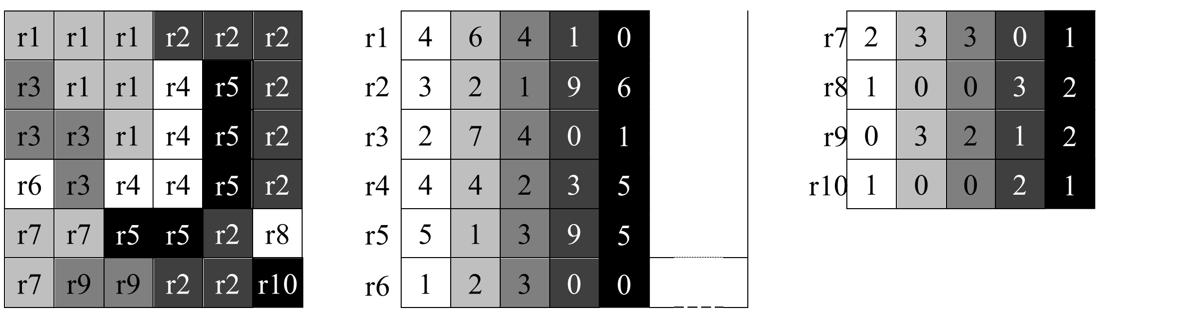


Figure 6. New data set

A SOM algorithm is then used for clustering the new data set. Each new region is assigned to a class according to the nearest node in the trained map. If necessary, the process of region aggregation and classification can be repeated in a recursive way to create new regions. Of course, due to the aggregation principle, the regions grow from one step to the following one.

Figure 7 illustrates three steps of the approach. The first step corresponds to the image shown in figure 2, and it is not reproduced here. The upper images of this figure represent the segmentation of the image into different classes of regions, where each grey level corresponds to a class. The lower images show the boundaries (white lines) of the extracted regions. Each unsupervised classification has been generated with a 3×3 Self Organizing Map learned during 40 epochs, using an aggregation radius of 1.5 at each step (an 8-connexity neighbourhood).

4.4. Discussion

As shown before, the segmentation of the data space, proposed by the Self Organizing Map, is not unique. All the learning processes, initialized with different random seeds, have produced slightly different classifications of the same regions. As a consequence, the image obtained by this classification method can be considered as propositions of regions.

The proposed concept extraction program can be used as a tool for remote sensing experts. The whole process is not computationally expensive. If we consider a simple stopping criterion, the unsupervised classification using Self Organizing Map has a complexity of O(n), where n corresponds to the number of examples. The region aggregation is not costly in terms of computing time provided that the information on the neighbourhood of the regions is kept in memory instead of being computed each time. This algorithm uses the distribution of classes in a region neighbourhood, and thus is not sensible to the rotation of the image. The region feature vector may be easily extended by more complex spatial properties or textural characteristics.

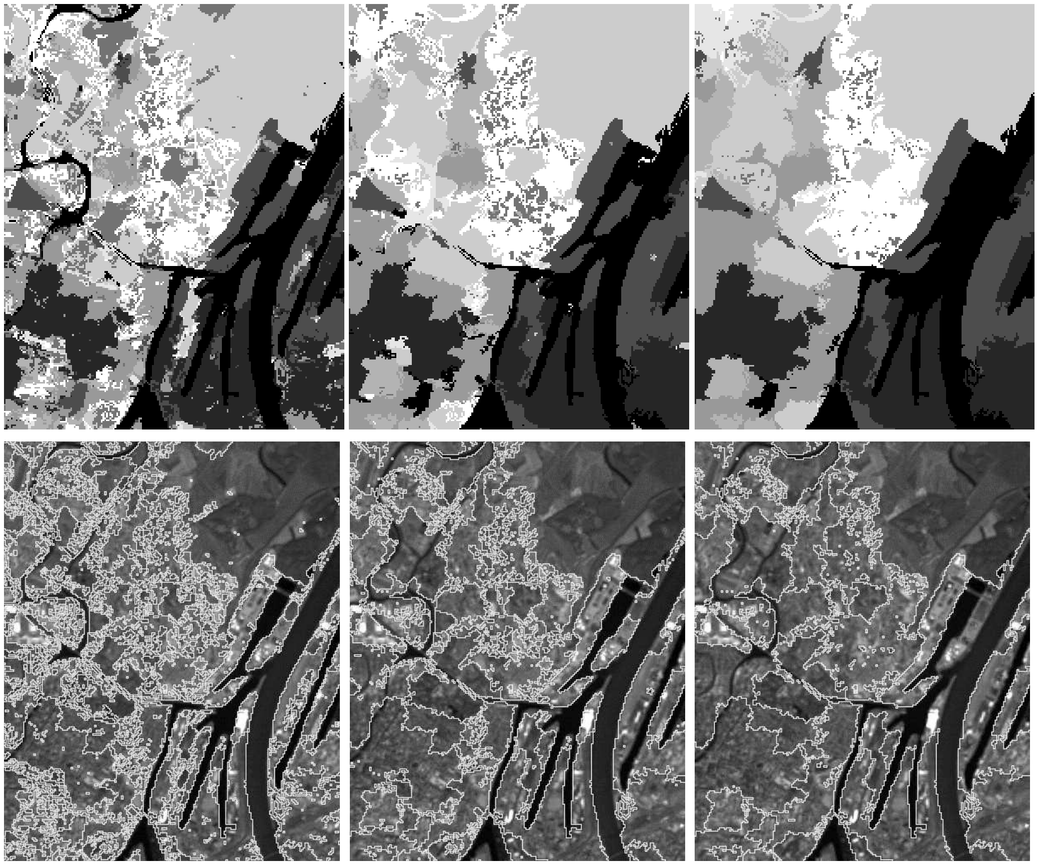


Figure 7. Three steps of the recursive process on an extract of Strasbourg 1986 data

A few points should be highlighted concerning our unsupervised learning method. Due to the choice of SOM, the classes, which are represented by a few number of regions, after the aggregation can be integrated into classes which are more frequently represented. This may occur when there are not enough classes available in the next step of classification for keeping these low represented regions. Nevertheless, since the successive results, from the spectral segmentation of the data space up to the highest level of regions are kept, the regions are not lost. Of course, the user may work with information of different aggregation levels corresponding to various semantics. This situation is illustrated in the images presented in figures 2 and 7. For example the Rhin river, at the right side of the images, was aggregated as one object in the first step, and later on at a bigger object corresponding to harbour installations or river neighbourhood.

5. CONCLUSIONS

A novel recursive unsupervised method, using both spectral and spatial information, has been presented and applied to SPOT image segmentation. The method is efficient in computing time and produces different levels of regions. The accuracy of the results and the simplicity of the method were found interesting by remote sensing experts.

The image segmentation algorithm is robust and independent of the domain knowledge.In general, there is no unique segmentation of an image. Different initializations of the algorithm may produce different segmentations of the data. The developed program is parametrized; the user can define the number of requested classes, and a region aggregation radius. Thus, by try-and-error, the user can test different parameter values for finding more accurate segmentations of the image.

The possibility of saving of successive region aggregations was appreciated by people working in the field of remote sensing. Indeed, the aggregation and classification processes impose the integration of the regions of weakly represented classes into strongly represented ones. In such cases, there is a risk of loosing the semantics of aggregated objects. Another point to underline is that at the same step, the different regions do not share the same level of semantic. We are currently working on this problem.

During the experimentations, it was noticed the importance of expert knowledge in the concept extraction process. Currently, we are trying to take into consideration other region features such as area, geometric form, regularity, texture characteristics, etc. It seems that it would be useful to introduce a weighting system to measure the relative importance of the region features in the classification process. Another promising approach towards image segmentation is the use of supervised neural network and rule extraction techniques which could help to verify and refine specific domain knowledge.

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