Multiscale Object-Based Classification of Satellite Images Merging Multispectral Information with Panchromatic Textural Features

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Abstract. Once admitted the advantages of object-based classification compared to pixel-based classification; the need of simple and affordable methods to define and characterize objects to be classified, appears. This paper presents a new methodology for the identification and characterization of objects at different scales, through the integration of spectral information provided by the multispectral image, and textural information from the corresponding panchromatic image. In this way, it has defined a set of objects that yields a simplified representation of the information contained in the two source images. These objects can be characterized by different attributes that allow discriminating between different spectral&textural patterns. This methodology facilitates information processing, from a conceptual and computational point of view. Thus the vectors of attributes defined can be used directly as training pattern input for certain classifiers, as for example artificial neural networks. Growing Cell Structures have been used to classify the merged information.

Keywords. Object attributes, Object-based classification, Wavelet coefficients, Segmentation, Lacunarity, Growing Cell Structures.

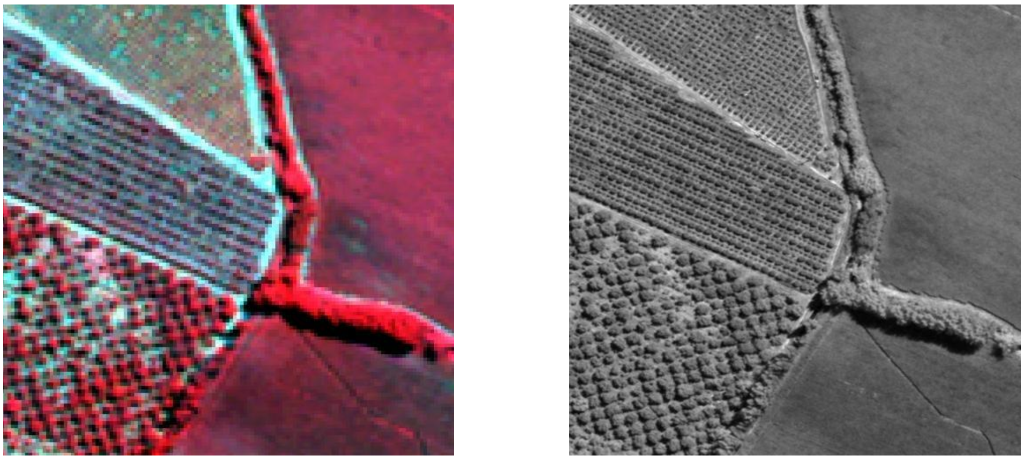
1. Introduction

Classification algorithms for multispectral remote sensing images can be categorized according different criteria. One of these is if the algorithm is pixel-based or object-based. When the first type of algorithms is applied to high-resolution remote sensing imagery, two main problems emerge. Very often, the *pepper and salt* effect appears in the classified image, due to the high variability of each spectral class in the original image. Furthermore, the limited number of spectral bands of such images results in a low separability between land covers [1], [2]. That means the thematic classes can not be discriminated through the multispectral image information. On the other hand, it is well known that the human visual system is not based on individual elements (pixel), but on the perception of objects characterized by different attributes (size, shape, texture, color,...). This is one reason why it is widely accepted that classification strategies based on objects can reduce the disadvantages of the methods of classification pixel by pixel in high-resolution space imagery.

In this type of processing, a critical step is the definition and characterization of objects, by clustering neighboring pixels with spectral and textural similar characteristics, in homogeneous and significant areas, from the standpoint of the end user. This clustering process, known as segmentation, must be adapted to the resolution and the scale of objects for each particular problem. Thus, in this paper, it is proposed a new methodology to carry out the definition of multi-scale objects. Homogeneous spectral objects are defined from the multispectral image and homogeneous textural objects from the Wavelet coefficients of the corresponding panchromatic image. This way to define the homogenous textural objects supplies an objects characterization at different scales, one for each Wavelet Transformation level, which is very useful to process scenes with different kind of land covers. The integration of these two sets of objects gives a set of multi-scale spectrally and texturally homogeneous objects. They can be characterized by different attributes, allowing discrimination of different spatial&spectral patterns. Unsupervised artificial neural networks based on Growing Cell Structures (GCS) [3] have been used for objects classification. Vectors of attributes for each object have been used as training patterns input in GCS.

2. Methods and materials

A scene of a Quickbird image, recorded on the February 18, 2005, in the region of O'Higgins, Peumo Valley, Chile (34º 18' 11" S, 71º 19' 11" W), has been used to illustrate the methodology proposed in this work. The panchromatic image size is 512x 512 pixels, corresponding to an area of 9.43 hectares. Fig. 1 a) shows a color composition (Near Infrared-Green-Blue) of the multispectral scene and Fig. 1 b), the panchromatic scene. Five spectral classes have been identified in this scene. Panchromatic and multispectral images have been geo-referenced each other to ensure a proper fit between them.



a) b)

Figure 1: Quickbird scene: (a) NIGB colour composite multispectral image; (b) panchromatic image.

The proposed methodology does not require other pre-processing methods. Fig. 2 displays a scheme of the proposed methodology described below. The higher spatial resolution of the panchromatic image justifies its use for defining objects from a morphological point of view; however, these objects can be spectrally and texturally heterogeneous, at least at some scale. With the aim of avoiding the influence of the spectral information from the panchromatic image, the Wavelet-*à trous* transform [4] of this image has been generated, and the obtained coefficients segmented for defining homogeneous textural objects (textural objects). The segmentation algorithm is based on Otsu' method [5]. By this method it is possible to choose an optimal threshold by maximizing the variance between classes by means a search throughout the image. In addition, the use of Wavelet coefficients, for determining textural objects, allows defining them at different scales, one for each coefficient level. The scale or resolution level to use will depend on the particular image as well as the objective of the final application. For determining homogeneous spectral objects (spectral objects), the pair of spectral bands with lower correlation has been chosen in order to determine, in the corresponding scattergram, spectrally homogenous areas, which have been spatially mapped in the multispectral image (pre-classification). The integration of these two types of objects, spectral and textural, yields objects with a spectral and textural particular behavior pattern. As a result of this process, n_k (k = number of levels of Wavelet transform) objects have been obtained for each scale or level.

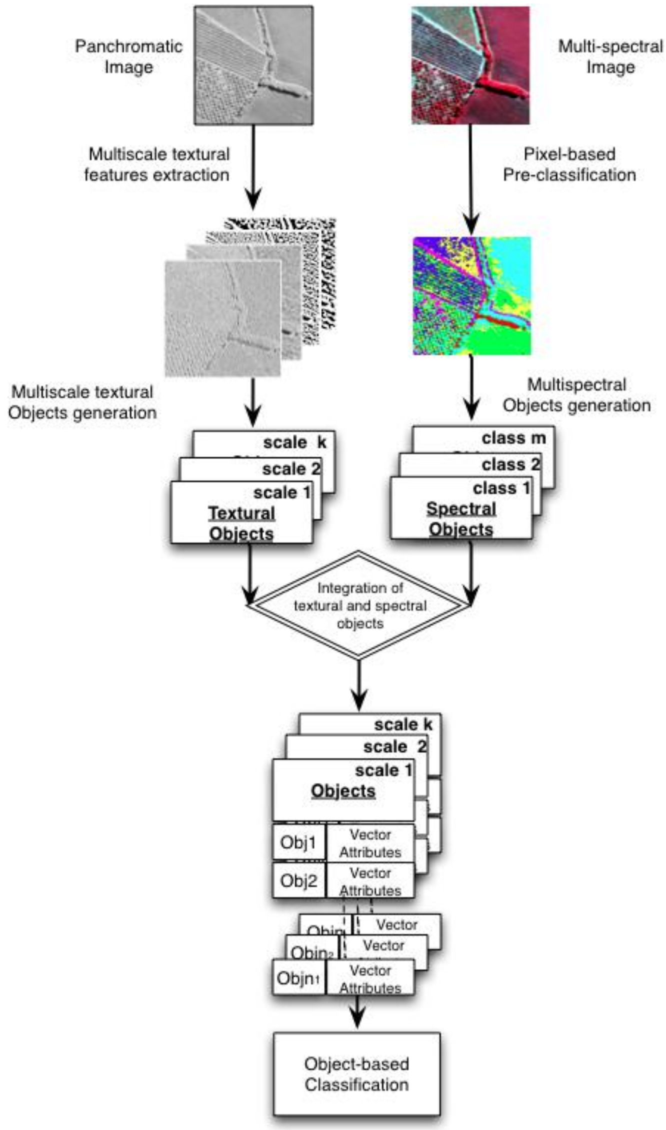


Figure 2: Multiscale objects generation and characterization

Once multi-scale objects have determined, they must be characterized by a set of textural and spectral attributes. These will depend on the scene under study and the application. In this way, each object is defined by the positions (row and column) of the pixels included in it, as well as an attributes vector, providing a joint and simplified representation of the information contained in both source images.

The attributes considered in a first approach, are mean values and standard deviations of the gray levels of each object for each spectral band, as well as, mean values and standard deviations of Wavelet coefficients and Lacunarity of each object for different scales. Since Lacunarity is a measure of how data fills space [6], it complements Wavelet coefficients, which detects details in the image. Many other spectral and textural attributes can be used. This way of representing the information reduces the number of data to be processed from 1.310.720 (512x512x5) to 33.920, considering three scales and ten attributes.

2.1. Multiscale object-based classification

Each attributes vector associated with an object has been used as a training pattern input into the GCS [7] used in this work for unsupervised classification. GCS is a two-layer architecture network. Neurons located at the input layer are fully connected with those in the output one. These connections have associated a weight, w_{ij}, where i identify the input neuron and j the output one. There exist as many input neurons as dimension has the input vectors (attributes). Neurons in the output layer have neighborhood connections between them presenting a topology formed by groups of basic t-dimensional hyper-tetrahedrons structures.

In this work the modification of the GCS training algorithm proposed in [4] has been used. The learning phase in GCS network adapts synaptic vectors looking for that each output neuron represents a group of similar input patterns. At the beginning of the training phase the output layer of the network has only three neurons interconnected via neighbor relations ($t=2$). During the learning process a set of input patterns is presented to the network iteratively. In each adaptation step an input pattern is processed, the synaptic vectors and its topological neighbor's synaptic vectors are modified, in order to slightly approach them to the pattern just processed.

3. Results

The methodology described above and illustrated in Fig. 2, has been applied to images displayed in Fig. 1 (a and b).

Wavelet coefficients *à trous* of panchromatic image have been generated for the first three levels. Then, textural objects have been generated by the Otsu method. Since this method allows limiting the minimum objects size, experiments with different values have been carried out (5, 25 and 50). Spectral objects have been generated by selecting five different homogeneous spectral regions in B3-B4 scattergram (spectral objects). These cover the whole image. In this paper, the integration of textural and spectral object has been done by mean the intersection between these two types of objects. However, other integration processes should be investigated. Table1 summarizes the number of objects obtained for each scale and for different values of minimum size of textural objects.

Table 1. Objects number.

Minimum size of objects	Scale 1	Scale 2	Scale 3
5	3334	531	316
25	2782	350	260
50	2696	265	221

Several experiments have been conducted for the different sets of objects, which were characterized with distinct sub-sets of spectral and textural attributes indicated above. Results displayed in this paper correspond to the objects obtained for a minimum textural object size of 50 (third row of Table 1). Vectors of attributes have been defined with six components: mean values of the gray levels of each object for each spectral band, mean value of Wavelet coefficients for the considered scale and mean value of Lacunarity, calculated with a window size of 15. A different GCS has been trained for each set of objects associated to a scale of the Wavelet Transformation. That is, all vectors of attributes of the objects associated to a scale have been used as training pattern input of a GCS. And they has been forced to be clustered in five different groups in order to visually compare results with a pixel-based classified image (Fig. 4 a). A further spatialization of the classification results have given the classified images displayed at Fig. 4 (b, c and d). It should be noted that the determined classes by the object-based classification method do not have the same meaning that the spectral classes of pixel-based classified image. Similar colors have been selected for both for better interpretation. In a visual comparison, it can be appreciated that the object-based classification method is able to detect the presence of vegetation (red color) on the roads (yellow color), while the pixel-based classified image is not. About growing areas (see Fig. 1 b), it can be seen that a better separation between vegetation (red), soil (green) and shadow (blue) is provided by the object-base classified images that for the pixel-based classified image.

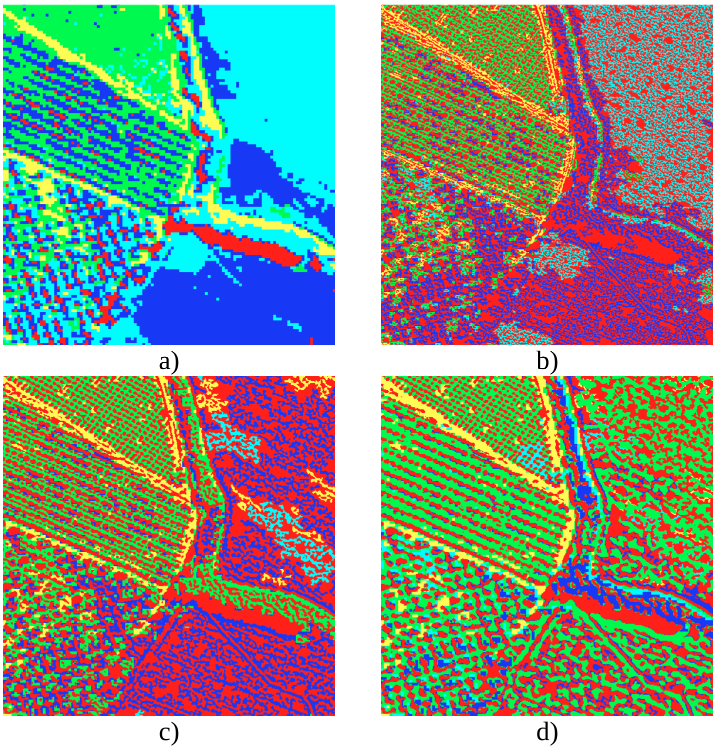


Figure 3: Pixel-based classified image. (b), (c) and (d) object-based classified images for three Wavelet levels.

Zooms for three different growing areas of these images have been included in Fig. 3. There, it can be appreciated that the proposed method allows isolating trees in the three areas. However, it seems that the first scale is over-segmented. Further investigations must be conducted to reduce this effect.

4. Conclusions

In this work, it has proposed a methodology that allows the identification and characterization of objects into a satellite scene, by merging information supplied by images with different spatial and spectral resolution.

The set of objects and theirs vectors of attributes gives a simplified and joint representation of the information contained in the two source images used in this case (multispectral and panchromatic images). This representation facilitates the processing of such information, both from a conceptual standpoint, such as computational. Thus, these vectors of attributes have been used directly as input training patterns into a particular artificial neural network (Growing Cell Structures).

Preliminary unsupervised classification results have been included to show the potential of the proposed methodology. Now well, further investigations must be performed for enhancing it in all stages.

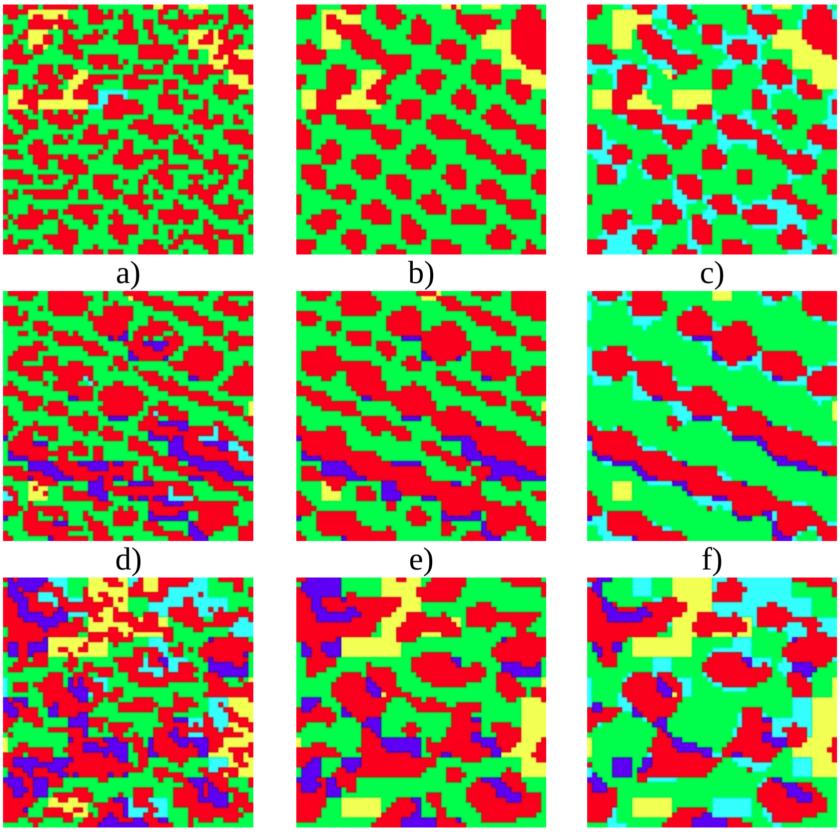


Figure 4: Zooms for three different areas of the image (rows) and for the three first Wavelet levels (columns).

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